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Satellite Image Restoration Using Shearlet Transform

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Abstract— A satellite image restoration method that avoids ringing artifacts at the image boundary and retains oriented features. The method combines periodic plus smooth image decomposition with complex wavelet packet transforms. The framework first decomposes a degraded satellite image into the sum of a “periodic component” and a “smooth component”. The Bayesian method is then used to estimate the modulation transfer function degradation parameters and the noise. Using complex wavelet packet transform the periodic component is deconvoluted and the result of the periodic component is combined with the smooth component to get the final recovered result. And also using shearlet transform the periodic component is deconvoluted composed with the smooth component to get recovered result is better than other methods. This test effectively avoids ringing artifacts and discontinuities while preserving local image details (especially direcional textures) without amplifying the noise.

Index Terms— Adaptive restoration, Complex wavelet packet transform, Deconvolution, Periodic plus smooth image decomposition,Shearlet transform,Signal composition.

1 Introduction

IMAGE restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as motion blur, noise and camera misfocus. It is concerned with filtering the observed image to minimize the effect of degradations. Effectiveness of image restoration depends on the extent and accuracy of the knowledge of degradation process as well as on filter design. Satellite image restoration can be classified into monoscale and multiscale techniques. However monoscale approaches have the drawbacks that they do not preserve strongly oriented textures and local details and may produce some artifacts. Unlike monoscale methods, multiscale approaches are mostly based on wavelet transforms (e.g., real wavelets and wavelet packets). These multiscale methods have the advantage that they can recover local textures without amplifying noise and provide a very fast implementation without iterations. Satellite image restoration has some difficulties such as (1) Ringing artifact (2) Noise Amplification (3) strong oriented textures. This paper presents an integrated approach to solve these problems that combines periodic plus smooth image decomposition into an image restoration method that suppresses ringing artifacts at the image boundary. The framework has the following steps. First the Satellite images are preprocessed to remove noise in the image. Secondly the image is decomposed into “periodic component” and “smooth component”, then Deconvolution process is applied to the periodic component. In Deconvolution process Complex Wavelet packet transform is used. Finally the smooth component is combined with the deconvoluted periodic coponent to obtain the restoration result.

2 Existing method

Previously, satellite image restoration can be classified into two techniques. They are, monoscale technique and multiscale techniques. Monoscale method include’s Wiener method, Bayesian based iterative method, MCMC maximum likelihood method. Multiscale methods based on wavelet transform. It includes Real wavelet, wavelet packets.

2.1 Wiener method

Combining ideas from statistics and time series analysis, Wiener used Gauss's method of shaping the characteristic of a detector to allow for the maximal recognition of signals in the presence of noise. This method came to be known as the "Wiener filter". The Wiener filter is a filter used to produce an estimate of a desired or target random process by linear time-invariant filtering an observed noisy process, assuming known stationary signal and noise spectra, and additive noise. The Wiener filter minimizes the mean square error between the estimated random process and the desired process. 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 frequency response. However, the design of the Wiener filter takes a different approach. 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 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).

This Wiener filter is frequently used in the process of Deconvolution.

2.2 Bayesian based iterative method

A restoration method of the degraded images based on Bayesian-based iterative method is proposed. An iterative method is developed by treating images, point spread functions, and degraded images as probability measures and by

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applying Baye's theorem. The method functions effectively in the presence of noise and is adaptable to computer operation. The present method for enhancement of images is to use the Bayesian rule. The Bayesian rule reflects optimal estimation in a sense to minimize the cost function under noisy observation and an iterative algorithm was proposed to find the optimal solution. The algorithm include two parts, the first one is to estimate a point spread function (PSF) from the estimated image and the second one is to estimate the original image by using the estimated PSF. Thus, this algorithm might be optimal when the observed image is similar to the original image, that is, in case of a high S/N ratio. Therefore, the results will depend on the initial guesses of PSF.

2.3 MCMC maximum –likelihood method

To estimate the optimal parameters in order to automatically reconstruct the image maximum likelihood estimator is used. Markov Chain Monto Carlo maximum likelihood (MCMC ML). MCMC ML TECHNIQUE able to simultaneously achieve the hyper parameter estimation and image deblurring. The satellite image deconvolution problem is ill-posed and must be regularized. To estimate the optimal parameters in order to automatically reconstruct the images, maximum-likelihood estimator (MLE) is applied to the observed images. Markov Chain Monto Carlo Maximum Likelihood (MCMC ML) technique which is able to simultaneously achieve the estimation and reconstruction.

2.4 Multiscale Method (Wavelet Packets)

Multiscale technique based on the wavelet transforms. It Includes wavelet packets. Wavelet packet transform (WPT) is a generalization of the dyadic wavelet transform (DWT) that offers a rich set of decomposition structures. WPT is associated with a best basis selection algorithm. The best basis selection algorithm decides a decomposition structure among the library of possible bases, by measuring a data dependent cost function. The number of nonzero coefficients after thresholding is used as the cost function. MSE or entropy has been the other choices, but none of them provided rate distortion optimization for image compression problem.

3 Proposed Method

The Proposed Algorithms are Periodic plus Smooth image decomposition and Complex Wavelet packet transform. This periodic Plus Smooth image decomposition method that suppresses the Ringing artifacts at the image boundary and complex wavelet packets are used to deconvolute the images that retains the directional textures and details without noise amplification.

3.1 Goal and objective

To remove the ringing artifact effects in the Satellite images.
To increase the efficiency of the algorithm.
To restore the Satellite images in a better way.
To deconvolute each sub band of the Satellite image.

3.2 proposed work overview

The Satellite images are first preprocessed to remove noise in the image. Then the image is decomposed into periodic and smoothing component. Deconvolution is applied to periodic component. For Deconvolution process we use Complex wavelet packet transform (CWPT).Then the smoothing component is combined with the deconvoluted periodic component. The resulting image is the restored Satellite image. And also we have implemented the shearlet transform in the Deconvolution process. Then PSNR and SSIM values are compared for CWPT and SHEARLET.

2.3 Periodic plus smooth image decomposition

The sum of a periodic component and a smooth component can be denoted as

$$U = P + S \qquad (1)$$

P+S decomposition can avoid some artifacts caused by discontinuities across the frame border in the frequency domain. The P+S decomposition can be combined with complex wavelet packets to improve satellite image restoration. The expression used is,

$$per(u)(q,r) = \hat{U}(q,r) - \frac{\hat{v}(q,r)}{4 - 2\cos\left(\frac{2\Pi q}{M}\right) - 2\cos\left(\frac{2\Pi r}{M}\right) - \hat{v}(q,r)} \qquad (2)$$

And per(u)(0,0)=ȗ(0,0),where v1=v1+v2 and ∀(x,y)Ω

- $$V1(x,y)=\begin{cases} u(x,y) - u(M-1-x,y), \\ \quad if\ x = 0\ or\ x = M-1; \\ \quad else \\ 0 \end{cases}$$
- $$V2(x,y)=\begin{cases} u(x,y) - u(x,N-1-y) \\ \quad if\ y = 0\ or\ y = N-1; \\ \quad else \\ 0 \end{cases}$$

(3)

From these equations (3), periodic component P=per(u) and smooth component S=U-P.

3.4 Deconvolution using Complex wavelet packet transform.

Complex Wavelet Transform is a complex-valued extension to the standard discrete wavelet transform (DWT). It is a two-dimensional wavelet transform.It Provides multiresolution, sparse representation, and useful characterization of the structure of an image. when compared with the multiscale approaches, CWPT has the advantage of packet decomposition and also has the interesting properties of complex wavelet transform. This CWPT is suitable for image restoration. The strategy of this paper is to deconvolute original image using CWPT to obtain adaptive denoising for each sub band. In each sub band signals Deconvolution process is applied. In each sub band noise variance σk^2 is estimated by blur Kernel H and σ^2.

$$\sigma k^2 = \sigma^2 x \sum i,j \left| F(Wk)i,j / F(H)i,j \right|^2 \qquad (4)$$

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where Wk is the impulse response signal of sub band k. The noise model of the sub bands gives the following probability distribution

$$P(x_o-\xi)=\exp\left[\frac{-\,|x_0-\xi|^2}{2\sigma k^2}\right]\Big/ 2\Pi S^2 \qquad (5)$$

Where x0 is the signal with noise and the prior probability of ξ is given by,

$$P(\xi\,|\,s)=\exp\left[-|\xi|^2 \big/ 2s^2\right]\Big/ 2\Pi s^2 \qquad (6)$$

Equation 5 & 6 with the maximum likelihood estimate gives,

$$\xi=x_0 \times s^2 \big/ (S^2+\sigma_k^2) \qquad (7)$$

where s is the estimate of the original signal.
Then s is obtained by adapting the Wiener filter to get the approximation ξ ', using a thresholding process as follows

$$\begin{aligned} s^2 &= |\xi'|^2 \big/ 4-\sigma' k^2, && \text{if } |\xi'| > 4\,\sigma' k2 \\ s^2 &= 0, && \text{if } |\xi'| < 4\,\sigma' k2 \end{aligned} \qquad (8)$$

where σ'k2 is the estimated variance of ξ', which could be replaced by σk2.Equations (7) and (8) can be used to obtain all the values of the parameter ξ for the sub bands, with the inverse CWPT used to get the restoration result.

3.5 Deconvolution using Shearlet transform.

Shearlet transform is a multidimensional version of wavelet transform. It is Optimal in representing the images with edges. This shearlet is Used in edge analysis and detection. Highly effective in detecting both the location and orientation of edges. This Shearlet transform is used in the Deconvolution process instead of using complex wavelet packet transform(CWPT). The properties of shearlet transform are, The system forms an affine system, The transform can be regarded as matrix coefficients, and there is an MRA structure associated with the system. Shearlet satisfies these properties to show the optimal behavior and the detection of directional information.
The expression of Mother Shearlet function is

$$\psi(\xi 1, \xi 2)=\psi 1(\xi 1)\psi 2(\xi 2/\xi 1) \qquad (9)$$

It is defined by three parameter, scaling parameter, shear parameter and translation parameter. whereas traditional wavelet transform associated with scaling and translation parameter.

- scaling parameter→ $\begin{pmatrix} a & 0 \\ 0 & \sqrt{a} \end{pmatrix}$
- shear parameter → $\begin{pmatrix} 1 & s \\ 0 & 1 \end{pmatrix}$
- translation parameter→t

Here in this shearlet implementation the maximum levels of sub band decomposition is identified using the below formula

Levels=floor(max(lseed*(1-1/d-log2(c)),0))
lseed=1:floor(log2(min(size(x))))-4 (10)

In each subband levels shearlet function is applied. In this shearlet function level check is maintained, denoted as S. To obtain the deconvoluted image inverse shearlet function is taken. The deconvoluted image is composed with the smooth component to provide the restoration result. In this, restored image avoids the discontinuities at the edges and provides the clear image details compared with CWPT. This Deconvolution using shearlet transform gives better PSNR and SSIM value.

3.6 Block diagram

The below block diagram Fig(1) shows the proposed work overview. In this block, P+S decomposition method is used to decompose the satellite image. And CWPT algorithm is used in the Deconvolution process. The Satellite images are first preprocessed using median filter to remove noise in the image. Then the image is decomposed into periodic and smoothing component. Deconvolution is applied to periodic component. For Deconvolution we use Complex wavelet packet transform (CWPT) and shearlet transform. Then the smoothing component is combined with deconvoluted image to provide the restored result.

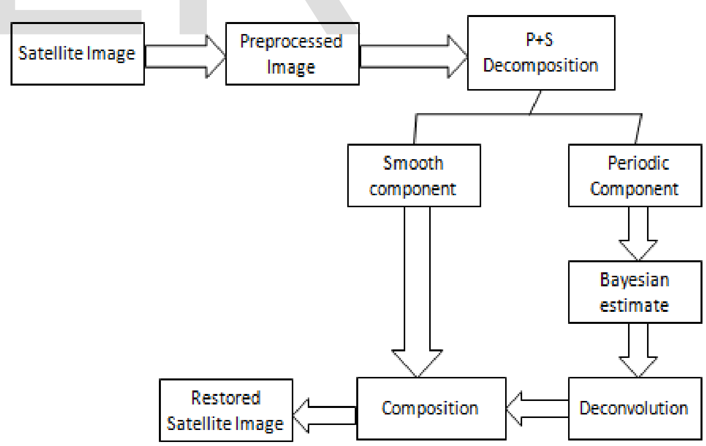

Fig (1) Algorithm overview

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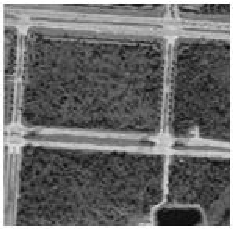
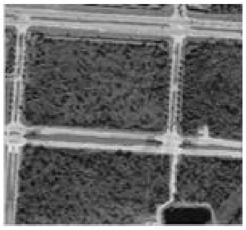
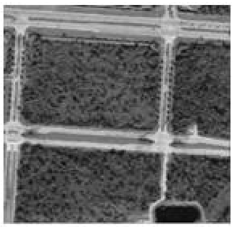
4 Results and Discussion

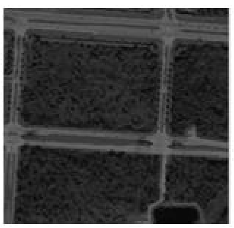
In Fig (2) shows the results of 2.1) blurred and noisy input image, 2.2) Preprocessed image, 2.3) Periodic component, 2.4) Smooth component image, 2.5) Deconvoluted image, 2.6) Restoration result.


2.1)Input image


2.2)Preprocessed image


2.3)Periodic component


2.4)Smooth component


2.5)Deconvoluted image

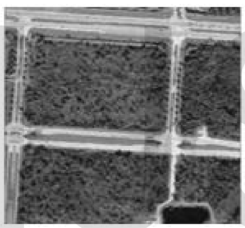
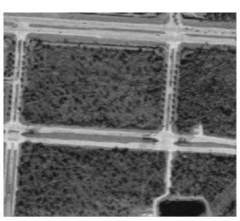
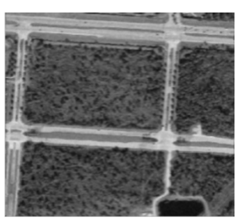
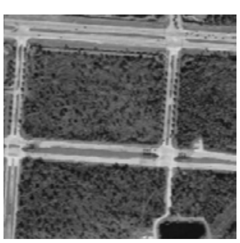

2.6)Restoration result

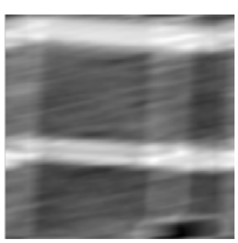
Fig 2 Deconvolution using CWPT

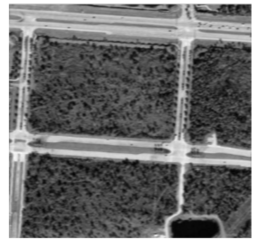
In Fig (3) shows the results of 3.1) blurred and noisy input image, 3.2) Preprocessed image, 3.3) Periodic component. 3.4) Smooth component image, 3.5) Deconvoluted image, and 3.6) Restoration result for Deconvolution using shearlet transform.


3.1)Input image


3.2)Preprocessed image


3.3)Periodic component


3.4)Smooth component


3.5)Deconvoluted image


3.6)Restoration result

Fig 3 Deconvolution using shearlet

5 Performance Analysis

The below tabulation shows result of PSNR and SSIM Values for deconvolution using CWPT and deconvolution using shearlet transform.The obtained PSNR and SSIM value is better for deconvolution using shearlet transform than Complex wavelet packet transform.The following tabulation shows the PSNR(Peak signal to noise Ratio)and SSIM(structural similarity) values for different algorithm using satellite images.structural structural similarity is a method for measuring the similarity between the images.

TABLE 1
SSIM and PSNR for Fig(2) and Fig(3)

Input images	**PSNR**	**SSIM**
Deconvolution using CWPT	23.7126	67.9039
Deconvolution using Shearlet	68.4712	96.7264

6 Conclusion

This paper presents an integrated approach for satellite image adaptive restoration. The Framework combines Periodic plus smooth decomposition with CWPT to avoid the ringing artifacts at the image boundaries and also shearlet Deconvolution is combined with P+S decomposition to avoid discontinuities at the edges of the satellite image and to provide better restoration result when comparing with CWPT Deconvolution by measuring the PSNR and SSIM values.This method can process large satellite images using parallel processing. The algorithm uses deconvolution based on CWPT and shearlet to obtain the original Image with adaptive denoising of each sub band, which retains directional textures and details without too much noise amplification.

This method shows the result of fewer ringing artifacts and avoids discontinuities at the edges gives the better image details than other methods. Application of this comparison shows that shearlet transform Deconvolution is better than CWPT Deconvolution and other methods.

REFERENCES

[1] Yan Zhang, Yiyun Man Satellite Image Adaptive Restoration Using Periodic Plus Smooth Image Decomposition and Complex Wavelet Packet Transforms ISSNll1007-0214ll16/18llpp337-343 Volume 17, Number 3, June 2012.
[2] Paul Escande, Pierre Weiss, and François Malgouyres (May 2013)'Image restoration using sparse approximations of spatially varying blur operators in the wavelet domain'.
[3] Mikael Carlavan, LaureBlanc-eraud, Marc Antonini, Carole Thiebaut, Christoophe Latry and Bobichon (April 28, 2013).'On the optimization of the satellite imaging chain'.
[4] Moissan L. Periodic plus smooth image decomposition. Journal of Mathematical Imaging and Vision, 2011, 39(2): 161-179.
[5] Lionel Moissan (October 2010) Periodic Plus Smooth Image Decomposition.
[6] ChoS, Lee S. Fast motion deblurring. ACM Transactions on Graphics (SIGGRAPH ASIA 2009), 2009, 28(5): paper 45.
[7] Shan Q, Jia J, Agarwala A. High-quality motion deblurring from a single image. ACM Transactions on Graphics, 2008, 27(3): paper 73.
[8] Jalobeanu A, Blanc-Feraud L, Zerubia J. Satellite image deblurring using complex wavelet packets. International Journal of Computer Vision, 2003, 51(3): 205-217.
[9] Jalobeanu A, Blanc-Feraud L, Zerubia J. Estimation of blur and noise parameters in remote sensing. In: Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing. Orlando, FL, USA: IEEE, 2002, 4:IV/3580-IV/3583.
[10] Jalobeanu A, Blanc-Feraud L, Jerubia J. Satellite image deconvolution using complex wavelet packets. In: Proceedings of the IEEE International Conference on Image Processing. Vancouver, Canada, 2000: 809-812.
[11] Vishal M. Patel, Member, IEEE, Glenn R. Easley, Member, IEEE, and Dennis M. Healy, Jr Shearlet-Based Deconvolution ieee transactions on image processing, vol. 18, no. 12, december 2009.
[12] On the optimization of the satellite imaging chain Mikael Carlavan, Laure Blanc-F´eraud, Marc Antonini, Carole Thiebaut, Christophe Latry and Yves Bobichon hal-00773606, version 1 - 14 Jan 2013.
[13] Nonseparable Shearlet Transform Wang-Q Lim IEEE TRANS 2013
[14] The Discrete Shearlet Transform: A New Directional Transform and Compactly Supported Shearlet Frames Wang-Q Lim IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 19, NO. 5, MAY 2010.