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Sparse Representation based Satellite Image Restoration Using Adaptive Reciprocal Cell

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Abstract

Recently, an emerging method called image sparse representation has attracted more attentions. The method has been proved to be effective in various image processing applications. It is important to note that few sparse representation methods fail to analyze the aliasing in satellite image restoration. To address the problem, firstly, we employ adaptive reciprocal cell as a image quality estimation tool, which can analyze the satellite image degradation factors including aliasing, blur and noise. Then, with the help of the powerful tool, the estimation about the satellite image quality is introduced into the sparse representation model . Experiment results show that our method can produce good quality restored results.

Keywords: *Image Restoration, Sparse Representation, Aliasing*

1. Introduction

In earth observation, sometimes there are no other images about the scene of interest but a single satellite image, usually corrupted by aliasing, blur and noise. Therefore, the image needs to be processed to better reflect its radiometric and geometric quality. This process is called satellite image restoration. Its goal is reconstruction or recovery of the degraded image using a prior knowledge of image degradation process [1-3].

Regularly, the discrete degradation model can be represented by

$$I = \Delta_{\Gamma} \cdot (h * f) + n \tag{1}$$

where I is the observed (measured) image. f is the natural scene, defined on a continuous support(a bounded set included in R^2). n is the additive Gaussian white noise. $(h * f)$ is the convolution product of f by the point-spread function h , which is normalized, positive and symmetric with respect to the x and y axes. The Fourier transform of h is called the MTF (Modulation Transfer Function). Actually, The effect of the imperfect optical system is characterized by MTF, which is similar to a low-pass filter leading to blurred appearance. Δ_{Γ} is the sampling comb composed of delta-functions δ_{ij} ,

$$\Delta_{\Gamma} = \sum_{(i,j)\in\Gamma} \delta_{ij} \tag{2}$$

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where Γ is the sampling grid. It represents the geometry of the array of sensors, which are assumed to be distributed on a regular grid:

$$\Gamma = \{n_1 e_1 + n_2 e_2 : n_1, n_2 \in Z\} \tag{3}$$

where $\{e_1, e_2\}$ is a basis of R^2. For square sampling grid Γ_4, $e_1 = (1,0)^T$,and $e_2 = (0,1)^T$. since $\langle \delta_{ij}, f \rangle = \int f(x)\delta_{ij} dx = f_{ij}$, sampling on Γ_4 can be expressed as simply multiplying by Δ_{Γ_4}.

The restoration of satellite image is an ill-posed inverse problem. It's well-known that direct inversion of (1) leads to unacceptable noise amplification. Therefore it is natural to address the limitations of direct methods by using advanced nonlinear regularization techniques which regularize the inversion problem so that the observed image can be recovered without amplifying the noise. Some related, wavelet-based satellite image restoration methods have been suggested in the literature [4-6], which can be summarized by the following two steps: deblurring by a pseudo-inverse filter, and then denoising done in a wavelet basis, by thresholding the noisy coefficients. Mainly, the differences between the two-step methods centered on the denoising are sparse representation algorithms [7-9]. Even if the two-step methods can resolve the denoising problem, they would be impractical. Since the optical system would be moving during capture, so that it would produce motion blurs which is invertible. It means that we can't even carry out the first step actually, otherwise ringing artifacts would arise.

F. Malgouyre and F. Guichard [10] have also observed the limitations of the wavelet-based methods and suggested to deblur satellite image using variational methods. The variational image resoration methods have been widely studied. Among them, the total variation (TV) regularization [11, 12] has become a popular method known for preserving discontinuities. Recently, an emerging method called sparse representation of image has attracted lots of attention [15, 16]. This theory has been proved to be effective in various application, such as image super-resolution [17], in painting [19], classification and image compression [13, 14].

In this work, we present adaptive reciprocal cell based image restoration which uses the advanced spare and redundant representation technology. The adaptive reciprocal cell is employed to analyze the degradation factors, such as blurring, noise and aliasing. Then, we introduce the analysis result into the sparse representation model.

2. Proposed Method

2.1. Adaptive Reciprocal Cell

According to signal sampling theory, (1) can be rewritten by Fourier transform:

$$\begin{cases} \tilde{I}(\tilde{X}) = \dfrac{1}{|\det V_s|} \sum_k \tilde{f}(\tilde{n} - U_a k) \\ U_a^T V_s = E \end{cases} \tag{4}$$

where U_a is the reciprocal cell which reflects the sampling period of satellite imaging system.

Based on the (4), [18] proposed the adaptive reciprocal cell method and used it to analyze the efficiency of various imaging system. This method can describe the aliasing in various imaging system, and is a new way of measuring the effective resolution of an image acquisition system.

2.2. Adaptive Reciprocal Cell based Sparse Representation Model

The traditional TV regularization model [20, 21] is effective in filtering the noise but tends to smooth the image, especially the image structure. This is due to the piecewise smoothing constraint. In recent years, the sparse representation related methods have achieved promising restoration results [22-24].Because of the high dimensionality of image, sparse representation method focuses on small patches of natural images. So the whole image is usually divided into image patches. Each image patch is processed independently, and the final result image is produced by stitching and averaging the patches.

The sparse representation model assume that an image patch f^p can be approximately represented via a vector α over a dictionary $\phi \in R^{n\times K}$ (each column in ϕ is called an atom). Image patch can be approximately represented as:

$$f^p \approx \phi\alpha, \qquad s.t. \qquad \|\alpha\|_0 \le T \tag{5}$$

where $\|\cdot\|_0$ is a pseudo norm that counts the number of nonzero items in vector α. (5) indicates that the sparse coding of f^p can be calculated by solving the l_0 minimization problem.

As the l_0 minimization problem is an NP problem, it is often resolved by l_1 problem which is convex. The related formulation is as follow:

$$\tilde{\alpha} = \arg\min_{\alpha} \left\{ \left\| f^p - \phi\alpha \right\|_2^2 + \beta \|\alpha\|_1 \right\} \tag{6}$$

where constant β is the regularization parameter, and the second term is sparse coding which is the sparse approximation process of f^p. In the view of image restoration, based on the (1), to recover f^p from I^p, f^p can be sparsely represented by solving the problem:

$$\tilde{\alpha} = \arg\min_{\alpha} \left\{ \left\| f^p - \Delta_\Gamma \cdot (h * \phi\alpha) \right\|_2^2 + \beta \|\alpha\|_1 \right\} \tag{7}$$

It is expected that $\tilde{\alpha}$ could be close enough to α. But due to the degradation factors, especially the aliasing, the restoration task is very challenging. Few sparse representation methods fully considered the aliasing, or rather analyzed the aliasing during their processing. Here, we employ the aliasing analysis tool, *i.e.*, adaptive reciprocal cell, to enhance the performance of sparse representation for image recovery.

We can rewrite the (7) as follow:

$$\tilde{\alpha} = \arg\min_{\alpha} \left\{ \left\| F(f^p) - F(h * \phi\alpha) \right\|_{\Omega_{arc}}^2 + \beta \|\alpha\|_1 \right\} \tag{8}$$

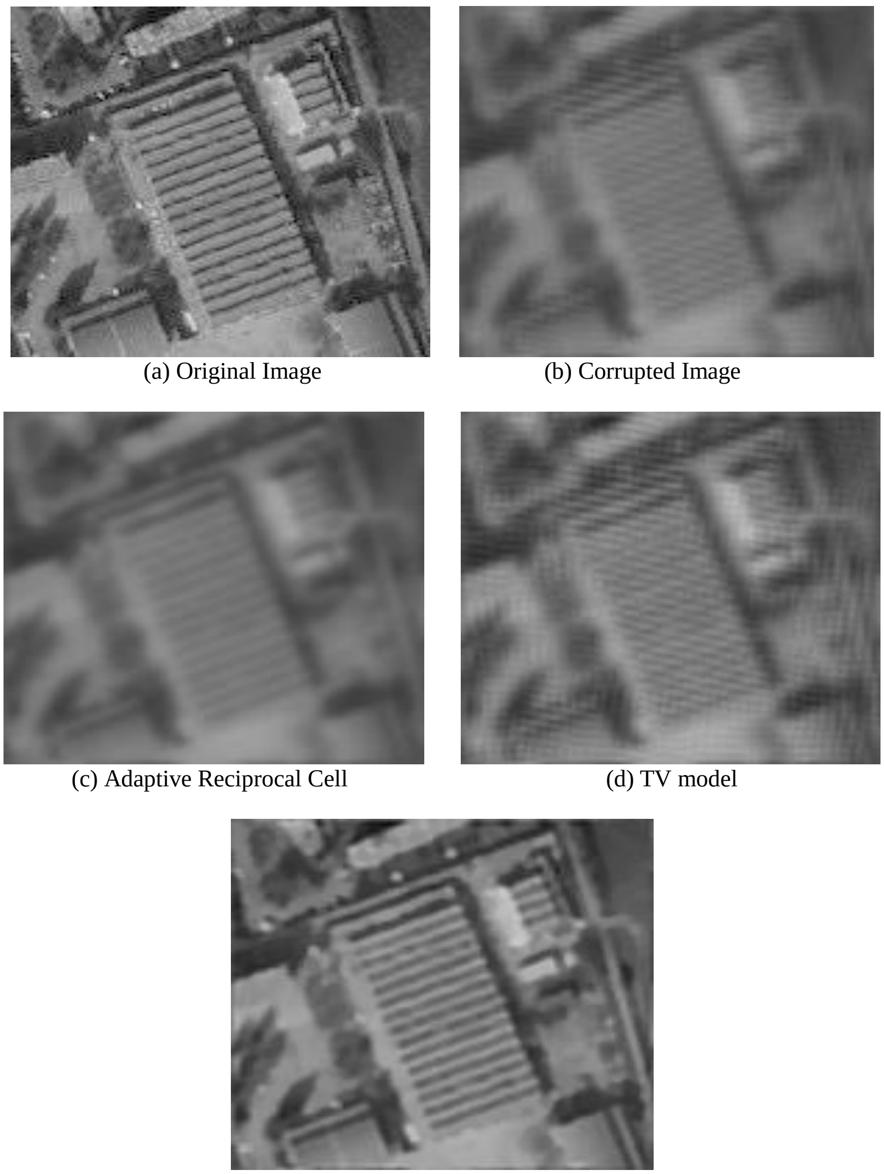
where $F(\cdot)$ stands for Fourier Transform. In(8), the data-fitting term is defined on the support region of adaptive reciprocal cell so that the model can effectively describe the aliasing.

3. Experimental Results

We applied restoration method to both simulated corrupted image and real CBERS-02B satellite image. In the simulated image restoration, a blur kernel, *i.e.* Gaussian function with standard deviation 2 is used. Then, Additive Gaussian noise with level 2 is added to the blurred image. After this, we the processed image is down sampling. The basic parameter setting of our proposed method is as follows: the patch size is 9×9 and $K = 120$.

In the experiment, the proposed method is compared with the TV model. As show in Figure 1.

Figure 1(a) is original image,(b) is degraded image, (c) is the image which is record by adaptive Reciprocal Cell, (d) is the restoration result of TV model and (e) is our method. We can see that the result of our method is clear and natural. We can also see the good performance of our method in Figure 2. In Figure 3, we use our method to process the real image, *i.e.* the CBERS-2B Satellite Image. We can see that our method can achieve good resotred image.

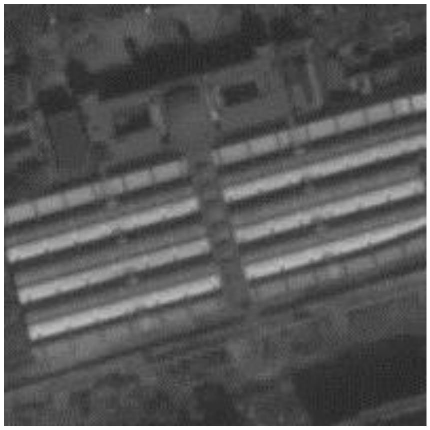


(a) Original Image (b) Corrupted Image

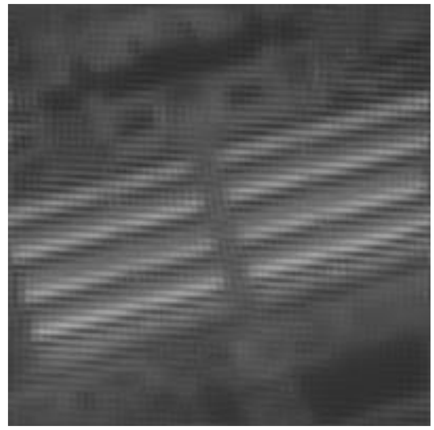
(c) Adaptive Reciprocal Cell (d) TV model

(e) Proposed method

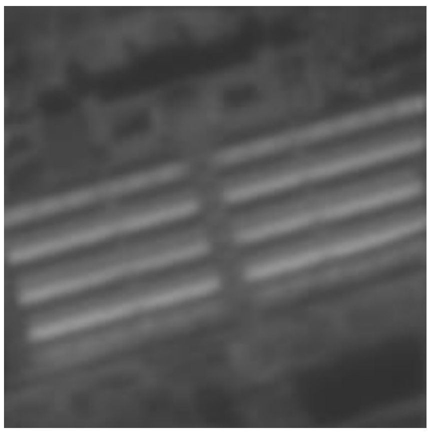
Figure 1. Simulated Image Restoration



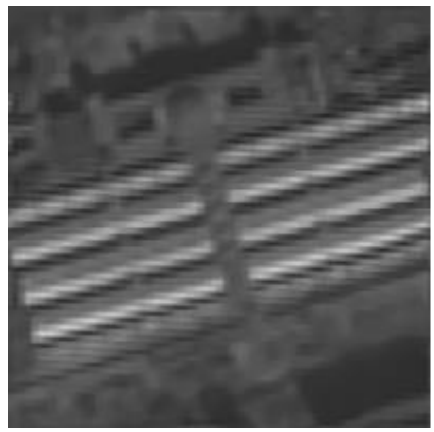
(a) Original Image



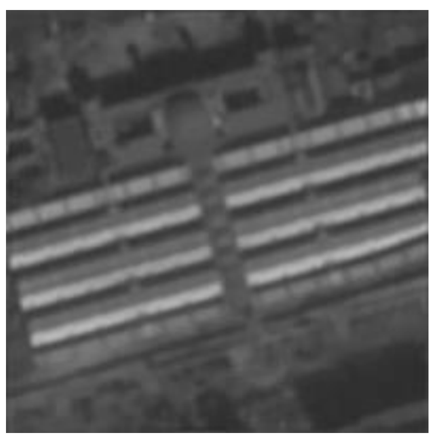
(b) Corrupted Image



(c) Adaptive Reciprocal Cell



(d) TV model



(e) Proposed method

Figure 2. Simulated Image Restoration

(a)Real satellite image (b) Proposed method

Figure 3. CBERS-2B Satellite Image Restoration

4. Discussions

In imaging process, high resolution satellite images are usually unavoidably corrupted by three degradation factors including blur, noise and aliasing. The satellite image restoration is an ill-posed inverse problem, which requires regularization to avoid unstable solutions. We have proposed a new sparse representation method for satellite image restoration by using the adaptive reciprocal cell to estimate the quality of the degraded image and then introducing it to restoration process in order to avoid amplifying noise. Experiment results show that our method can produce appealing results in vision.

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