HSI Image Restoration using Low Rank Matrix Recovery

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ABSTRACT

Restoration is process of undoing or recovering an image from degraded state. The image restoration techniques are used to make the corrupted image as similar as that of the original image. Hyper spectral image are often corrupted by a mixture of various kinds of noise in the acquisition process, which can include Gaussian noise, impulse noise, deadlines, stripes, and so on. Various restoration methods are used. A new HSI restoration method based on low-rank matrix recovery (LRMR) is introduced, which can simultaneously remove the Gaussian noise, impulse noise, deadlines, and stripes but there is no spatial constraint applied on neighbouring pixels that causes large areas of missing pixels. To handle the problem of missing pixels non-reference regularization algorithm is used.

Keywords

Image Restoration, HSI, Low Rank Matrix Recovery (LRMR)

1. INTRODUCTION

Restoration refers to various ways that has aim to decrease or eliminate the degradation that have occurred while the digital image was being obtained. The degradation might be due to several factors like relative object-camera motion, blur due to camera misfocus, relative atmospheric turbulence. So to overcome the degradation in the image, visibility restoration strategies are applied to the image so as to get a better quality of image. So the image restoration techniques are used to make the corrupted image as similar as that of the original image. Image enhancement is the process in which the degraded image is manipulated and the visual appearance of the image is improved. It increases the contrast of image and is subjective process. But image restoration is a more objective process than image enhancement. Hongyan Zhang[1] analysis Hyper spectral images (HSIs) that are often degraded by a mixture of various kinds of noise in the acquisition process, which can include Gaussian noise, impulse noise, deadlines, stripes, and so on. Because of that not only the visual appearance but also the applications of these images, which include urban planning, mapping, agriculture, forestry, and so on, are severely influenced. Therefore, as a pre-processing of the image application, HSI restoration is an active and challenging research area. This paper introduces a new HSI restoration method based on low-rank matrix recovery (LRMR), which can simultaneously remove the Gaussian noise, impulse noise, deadlines, and stripes.

1.1 RESTORATION METHODS

Various restoration methods are given for HSI. Traditional denoising methods treat each band of the HSI as a gray-level image and restore them separately. More advanced denoising techniques mainly use the spectral information of the HSI and

have achieved good results. For example, Letexier and Bourennane [2] considered the HSI data set as a third-order tensor and introduced a generalized multidimensional Wiener filter to denoise the HSIs. Liu *et al.* [3] developed a powerful multilinear algebra model named parallel factor analysis (PARAFAC) to denoise HSIs, and it has been shown that the PARAFAC model is an efficient denoising method for the removal of Gaussian noise from HSIs. Recently, researchers have paid most of their attention to the denoising methods that use the spatial and the spectral information together, and these approaches have made significant progress.

1.2 LRMR-Based HSI Restoration Model

The image restoration techniques are usually based upon various matrix level methods, where the images are first converted into the matrix before applying the restoration operations on them. In the existing scheme, the image restoration has been performed using the Low Rank Matrix Recovery (LRMR) method. The LRMR method compares the image matrix with the approximation matrix of the image to find the irregularity in the image data. The irregularity matrix is called the error matrix and subtracted from the original image to restore the image. The go decomposition or GoDec method will be used to create the cube of original image and its decomposed matrices.

The LRMR model was first proposed by Wright *et al.* [5] and is idealized as a “robust principal component analysis” (RPCA) problem. Assuming that a low-rank matrix $\mathbf{L} \in \mathbb{R}^{m \times n}$ is corrupted by a sparse error matrix $\mathbf{S} \in \mathbb{R}^{m \times n}$, then the observed data matrix $\mathbf{D} \in \mathbb{R}^{m \times n}$ can be decomposed as the sum of a sparse matrix and a low-rank matrix,

$$\text{i.e., } \mathbf{D} = \mathbf{L} + \mathbf{S}.$$

The ideal RPCA problem can be described as follows: Given the observed data matrix $\mathbf{D}$, the low-rank matrix $\mathbf{L}$ and the sparse error matrix $\mathbf{S}$ are unknown, and the goal is to recover $\mathbf{L}$. The formulation of this optimization problem is [5]

$$\text{Min } \mathbf{L}, \mathbf{S} \text{ rank}(\mathbf{L}) + \lambda \|\mathbf{S}\|_0 \text{ s.t } \mathbf{D} = \mathbf{L} + \mathbf{S}. \quad (1)$$

Unfortunately, (1) is a highly non convex optimization problem, and no efficient solution is known. We can obtain a tractable optimization problem by relaxing (1) and replacing the $\|\cdot\|_0$ -norm with the $\|\cdot\|_1$ -norm and the rank with the nuclear norm [6]–[8], yielding the following convex surrogate:

$$\text{Min } \mathbf{L}, \mathbf{S} \|\mathbf{L}\|_* + \lambda \|\mathbf{S}\|_1 \text{ s.t } \mathbf{D} = \mathbf{L} + \mathbf{S} \quad (2)$$

where λ is the regularization parameter used to balance the relative contribution between the nuclear norm and the $\|\cdot\|_1$ -norm. Candes *et al.* [9] have proven that, when the rank of the matrix $\mathbf{L}$ and the sparsity and distribution of $\mathbf{S}$ obey certain conditions, there is a high probability of recovering the low rank matrix $\mathbf{L}$ and sparse matrix $\mathbf{S}$.

1.3 Non Reference Regularization

Algorithm (NRRR)

During HSI restoration using LRMR, there is no spatial constraint applied on neighbouring pixels that causes large missing pixels. To recover missing pixel various algorithms can be used. The NRRR is used to recover the missing pixels. The recovery framework can be written as:

$$p = \operatorname{argmin} \left[\frac{E}{P} \right] \quad (3)$$

where

$$E(P) = \|Q(P - P')\|^2 + \lambda R(p); \quad (4)$$

is the cost function, in which p' and p represent the input primary image and the desired primary image, respectively, $R(p)$ represents the regularized model, and λ is the regularization parameter. Here, Q is diagonal matrix representing the reliable information in the different pixel locations, and its row number equals the image size. For the recovery issue, the element values are set to one for all the valid pixels, and to zero for the missing pixels. [10]

2. LITERATURE SURVEY

Tzikas, D.G. et. al. has worked on a new Bayesian model for the blind image deconvolution (BID) problem. In the proposed approach, a robust model of the BID preserves edges of the reconstructed image. Sparseness, robustness, and preservation of edges are achieved by using priors that are based on the Student's-t probability density function (PDF). **Zhang X. F et. al. [12] has implemented the regularized anisotropic diffusion filter.** In this paper, a regularized anisotropic diffusion filter was presented and USED to restore the DWI. The presented filtering strategy used for god preservation of edges. Rician noise, the PSNR and MOSIM metrics were used for measurement. Better results were found than conventional filters. **Xiaoli Lian et. al. has worked on** modified homomorphic deconvolution which is used in improvement in the quality of medical ultrasound image. The proposed deconvolution performs the filtering based on the estimation of the point-spread function (PSF). Especially, the application of a non-local means (NL-means) algorithm makes PSF estimation more precise for rejecting the White-Gaussian noise (WGN) effectively. They validate our method for different radio-frequency (RF) images with resolution improvement. **Mateos, J. et. al. has worked with** new Bayesian methodology for the restoration of blurred and noisy images. Bayesian methods based on encapsulating prior image knowledge of image and avoid the ill-posedness of image restoration problems. They use a spatially varying image prior utilizing a gamma-normal hyper prior distribution on the local precision parameters. The proposed restoration technique is better than other image.

3. PROPOSED METHODOLOGY

Image acquisition is the first step of the proposed model; image will be loaded in to the working memory of the image restoration model. After acquiring the image, the next step will be to perform the low-rank matrix restoration (LRMR) to restore the image. The go decomposition or GoDec method will be used to create the cube of original image and its decomposed matrices. Afterwards, the image would undergo the pixel level restoration using the non-reference regularization algorithm. This method will recover the missing pixel regions. Then New Edge-Directed Interpolation (NEDI) filter will be used to recover the pixel expansion problem occurred due to the image de-noising and restoration processes. Then, various performance parameters would be

obtained in the form of mean squared error (MSE), root mean squared error (RMSE), normalized absolute error (NAE), Structural similarity (SSIM) and peak signal to noise ratio (PSNR). The performance of the proposed model will be thoroughly studied in order to conclude the findings and the comparison of the proposed and existing models will be performed to evaluate the improvement in the performance of the proposed model.

4. CONCLUSION

In the paper, HSI Restoration is done using LRMR technique which include comparing the image matrix with the approximation matrix of the image to find the irregularity in the image data. The irregularity matrix is called the error matrix and subtracted from the original image to restore the image. The main advantage of the LRMR restoration algorithm is that all the Gaussian noise, impulse noise, deadlines, and stripes are taken into consideration. But there is further room for improvement, no spatial constraint is applied on neighbouring pixels that caused large missing pixel areas. So to improve NRRR is applied for recovering missing pixels.

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