HYPERSPECTRAL IMAGE INPAINTING BASED ON LOW-RANK REPRESENTATION: A CASE STUDY ON TIANGONG-1 DATA

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ABSTRACT

Hyperspectral images (HSIs) cover hundreds of narrow spectral bands, thus yielding high spectral resolution, enabling precise identification of different materials. However, the existence of dead pixels in the light sensors produces a number of irrelevant measurements, which may compromise the usefulness of HSIs. In this paper, a new hyperspectral inpainting method, named HyInpaint, is proposed. The original HSI is represented on a low dimensional subspace and its estimation is formalized with respect to the subspace representation coefficients on a given basis. The coefficients are estimated by minimizing an objective function which, in addition to the data term, contains a regularizer based on the Criminisi’s inpainting method. The optimization is carried out by an instance of the alternating direction method of multipliers (ADMM), adopting the plug-and-play methodology. The effectiveness of the proposed HyInpaint approach is illustrated on Tiangong-1 hyperspectral visible near infrared (VNIR) wavebands data.

Index Terms— Inpainting, hyperspectral image, low-rank representation, ADMM, Criminisi’s inpainting method, Tiangong-1 VNIR hyperspectral images

1. INTRODUCTION

Hyperspectral images (HSIs) provide hundreds or thousands of narrow spectral bands for each pixel, yielding a wealth of spatial and spectral information, enabling applications of HSI in, namely, environmental monitoring, mineral surveys, and remote surveillance. However, dead pixels, often existing in HSIs due to various malfunctions of the acquisition system during the scanning and transformation process [1], may limit the potential of the HSIs. The measurement in dead pixels does not have any correlation with the true radiance [2]. Continuous dead pixels affecting a large number of bands severely hamper the visual image perception and may preclude the use of the corrupted HSIs in subsequent applications. In order to improve the quality of degraded HSI, it is essential to restore the dead pixels, thus preserving the original information as much as possible.

HSI restoration is the process of hyperspectral image reconstruction from degraded observations. Interpolation and inpainting are two important kinds of image reconstruction methods designed to fill in the missing data [3]. Interpolation methods are often preferred for fast computation and data with small gaps; inpainting methods are often preferred for large unknown regions. Recently, a number of inpainting algorithms have been proposed for hyperspectral scenes. In [4], a method based on a maximum a posteriori probability inference was proposed for both destriping and inpainting problems; the use of an anisotropic diffusion inpainting model for hypercube was introduced in [1]. It is widely accepted that these inpainting algorithms are suitable for the situations where dead pixels just exist in a few bands or in small regions. However, the problem becomes more complicated where a considerable continuous region with dead pixels appears in many bands. Besides, the continuous dead pixels may appear along slanted directions, with respect to flight direction, which is more challenging than if the dead pixels are aligned along the horizontal or vertical directions.

A great deal of research work exploits the low-rank structure of clean HSIs [5-10]. Low-rank representation has proved its effectiveness in HSI processing in recent years. Taking advantage of the high correlation in adjacent bands and high data redundancy of spatial information, low-rank representation turns to find a low-rank matrix to approximate the high dimensional HSI, and obtain a compact and discriminative representation [5]. The work [6] provides evidence on how low-rank representations fit hyperspectral data, and [7,10] proposed a fast HSI denoising method based on low-rank and sparse representation.

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The existing HSI inpainting methods, assuming that only a few bands are corrupted, fail in the situation where continuous dead pixels affect most of the bands, and this research line remains relatively less explored. Therefore, this paper introduces an effective hyperspectral inpainting method, called HyInpaint, conceived for the HSI inpainting problems with dead pixels possibly affecting a large number of bands.

The paper is organized as follows. Section 2 introduces the proposed inpainting algorithm based on low-rank representation of HSI. Section 3 presents the experimental results with Tiangong-1 hyperspectral VNIR data. Section 4 concludes the paper with some remarks and future researches lines.

2. PROPOSED HYINPAINT METHOD

2.1. Low-rank structure of HSI

Let \( Y := [y_1, \ldots, y_n] \in \mathbb{R}^{n_r \times n} \) denotes the corrupted HSI with \( n \) spectral vectors (the columns of \( Y \)) of size \( n_b \) (the number of bands of the sensor). It is often natural or reasonable to assume that the observed HSI is the sum of a complete and
\[
X = \mathbf{E} \mathbf{Z},
\]

where \( X := [x_1, \ldots, x_n] \in \mathbb{R}^{n_b \times n} \) represents the original HSI and \( \mathbf{N} \in \mathbb{R}^{n_b \times n} \) is the additive noise. Work [8] provides evidence that, with very good approximation, the spectral vector \( x_i \), for \( i = 1, \ldots, n \), live in a \( p \)-dimensional subspace \( S_p \), with and \( n_b >> p \). Therefore, \( X \) can be expressed as
\[
X = \mathbf{E} \mathbf{Z},
\]

where \( \mathbf{E} = [e_1, \ldots, e_p] \in \mathbb{R}^{n_b \times p} \) holds the basis of subspace \( S_p \) and \( \mathbf{Z} = [z_1, \ldots, z_n] \in \mathbb{R}^{p \times n} \) is the representation coefficients of \( X \) with respect to \( E \). The rows of \( Z \in \mathbb{R}^{p \times n} \) are herein termed eigen-images.

2.2. Proposed HyInpaint method

We assume, without loss of generality, that \( E \) is semi-unitary, that is \( E^T E = I \) with \( I \) representing the identity matrix of appropriate size. A great deal of research has been devoted to find a lower dimensional subspace to express the observed HSI properly, such as principle components analysis (PCA) and singular value decomposition (SVD). Herein, we adopt hyperspectral signal subspace identification by minimum error (HySime) [9] method to project the high dimensional observed HSI to a lower dimensional subspace, since it is fully automatic and requires no tuning parameters. Given that the dead pixels do not live in the subspace with high probability, we do not use them in the subspace learning step.

Let \( M \in \mathbb{R}^{n_b \times n_b} \) be a diagonal matrix with diagonal elements [\( M \)]_{i,i} = 1 if the pixel \( i \) does not contain dead pixels and [\( M \)]_{i,i} = 0 otherwise. We assume that, if [\( M \)]_{i,i} = 0, all bands are corrupted in pixel \( i \), corresponding to the most challenging scenario described before. With this notation in place, the original eigen-images \( Z \) are estimated by solving the optimization
\[
\min_{\mathbf{Z}} \frac{1}{2} \| \mathbf{Y} - \mathbf{EZM} \|_F^2 + \lambda \phi(\mathbf{Z}),
\]

where \( \phi \) is a spatial regularizer acting on \( Z \) and \( \lambda > 0 \) is a regularization parameter. Assuming that \( \phi \) is decoupled w.r.t. the eigen-images, that is \( \phi(\mathbf{Z}) = \sum_{i=1}^{n} \phi(z_i) \), where \( z_i \in [\mathbf{Z}^T]_{i,i} \) is the \( i \)-th eigen-image (i.e., the \( i \)-th column of \( \mathbf{Z}^T \)), and having into consideration that \( \mathbf{E} \) is semi-unitary, then the optimization (3) can be written
\[
\min_{\mathbf{Z}} \frac{1}{2} \| \mathbf{y}_i' - \mathbf{MZ}_i \|_2^2 + \lambda \phi(z_i), \ i = 1, \ldots, p
\]

The augmented Lagrangian function for (5) is
\[
\min \frac{1}{2} \| \mathbf{y}_i' - \mathbf{MZ}_i \|_2^2 + \lambda \phi(z_i), \ s.t. \mathbf{v}_i = \mathbf{z}_i, \ i = 1, \ldots, p
\]

Algorithm 1 Solve optimization (4) via ADMM

1: Set \( k = 0, \lambda > 0, \mu > 0, \mathbf{v}_{i,k} = [\mathbf{Y}^T \mathbf{E}]_{i,i}, \mathbf{d}_k = 0 \)
2: repeat
3: \( \mathbf{z}_{i,k+1} = \mathbf{arg\min}_{\mathbf{z}_i} \| \mathbf{y}_i' - \mathbf{M} \mathbf{z}_i \|_2^2 + \mu \| \mathbf{z}_i - \mathbf{z}'_{i,k} \|_2^2 \), where \( \mathbf{z}'_{i,k} = \mathbf{v}_{i,k} + \mathbf{d}_k \)
4: \( \mathbf{v}_{i,k+1} = \mathbf{arg\min}_{\mathbf{v}_i} \lambda \phi(z_i) + \frac{\mu}{2} \| \mathbf{v}_i' - \mathbf{v}_i \|_2^2 \), where \( \mathbf{v}'_{i,k} = \mathbf{z}_{i,k+1} + \mathbf{d}_k \)
5: \( \mathbf{d}_{k+1} = \mathbf{d}_k - (\mathbf{z}_{i,k+1} - \mathbf{v}_{i,k+1}) \)
6: \( k \leftarrow k + 1 \)
7: until a stopping criterion is satisfied

In line 3 of Algorithm 1, a strictly convex quadratic function is minimized, which has a closed-form solution:
\[
\mathbf{z}_{i,k+1} = (\mathbf{M}^T \mathbf{M} + \mu \mathbf{I})^{-1} (\mathbf{M}^T \mathbf{y}_i' + \mu \mathbf{z}'_{i,k}), \quad (7)
\]

where \( \mathbf{z}'_{i,k} = \mathbf{v}_{i,k} + \mathbf{d}_k \). We remark that problem (7) is very light because the matrix to invert is diagonal.
In (6), the minimization with respect to $v_i$, is the proximity operator of $\phi_i$. Here, we adopt the plug-and-play strategy [11], which we implemented by applying the state-of-the-art Criminisi’s exemplar-based inpainting method [12], which was conceived to inpaint large objects. For further details on the plug-and-play strategy, including the convergence of obtained algorithm, see [11].

Finally, from the estimated inpainted eigen-images $\hat{Z} = [\hat{z}_1, ..., \hat{z}_p]^T \in \mathbb{R}^{p \times n}$, the desired version of $\hat{X}$ is obtained by computing

$$\hat{X} = E\hat{Z}. \quad (8)$$

3. EXPERIMENTS USING TG-1 HYPERSPECTRAL DATA

This paper puts a sharp focus on HSI inpainting problems where continuous dead pixels exist in a majority of the bands. As a case study, we consider the HSI data acquired by Tiangong-1(TG-1). TG-1 hyperspectral imager has the highest composite indicator of space imaging spectrometry in China; the sensor is a 128-band push broom scanner with nominal bandwidths of 10 nm visible near infrared (VNIR) and 23 nm short wave infrared (SWIR), covering a spectral range of 400-2500nm. The VNIR data offers a finer spatial resolution with 10m than other hyperspectral sensors carried on previous Earth observation satellites. Thus it is an important marked supplement to the only on-orbit HSI satellite sensor, the EO-1 Hyperion. Along with the launch of TG-1, the acquired HSI with a great improvement on spectral coverage, spectral resolution, and spatial resolution, has broaden the field of applications. Plenty of research efforts have been devoted to the use of TG-1 HSI data, such as mineral mapping, forest monitoring and urban land-cover classification. However, a non-ignorable part of continuous dead pixels appear in most of the bands in VNIR range. Fig.1 (a) is a TG-1 hyperspectral image with three obvious regions of continuous dead pixels. These dead pixels offer no useful signal and severely affect the visual effect and subsequent applications; Fig.1 (b) is the mean spectrum of ROI. The proposed HyInpaint method is particularly well suited to this problem scenario.

In order to test the performance of the proposed HyInpaint method, we conduct experiments on simulated data and real data, which both are subsets of the TG-1 hyperspectral image in VNIR range.

3.1. Simulated data experiments

In simulated experiments, we test the proposed HyInpaint method with a subset (of size $211 \times 207 \times 69$ ) of the TG-1 HSI, which is not corrupted by dead pixels. A seven pixels wide and an eight pixels wide long regions along the oblique direction of continuous dead pixels are artificially added, covering a spectral range of 402-1034nm. We perform inpainting of the dead pixels with ENVI Landsat-Gapfill tool, Criminisi’s inpainter, and the proposed HyInpaint. The first two methods were applied to every band. Fig.2 shows the results and illustrates the effectiveness of HyInpaint.

It is well-known that spectral shape is significant for hyperspectral data [13]. Hence the spectral signature is presented for qualitative assessment. Fig.3 shows the reference and recovered spectral signatures of a dead pixel situated in the middle the corrupted region, to illustrate the fidelity of the reconstructed signatures.

3.2. Real data experiments

In real data experiments, another subset (of size $211 \times 204 \times 69$) from TG-1 HSI, which is truly corrupted by continuous dead pixels is employed. Due to the lack of ground reference of dead pixels, here we adopt the gray scale information from a SWIR band acquired by another sensor on TG-1, which is very close to the corresponding VNIR band and not corrupted by dead pixels, to compare the visual result. Fig.4 (a) is the reference SWIR gray image, Fig.4 (b) is the original corrupted image, Fig.4 (c)-(e) are the inpainting results, and Fig.4 (f)-(j) are the corresponding zoom-in images of (a)-(e). The proposed HyInp-
paint method yields, qualitatively, the best visual perception.

Experimental results illustrate that the proposed HyInpaint method can effectively solve the HSI inpainting problem with dead pixels which cover most of the bands. The inpainted HSI seems unaltered to an observer unacquainted with the original image. In addition, taking advantage of the low-rank structure of HSI, the Criminisi’s inpainting method is applied only to the eigen-images, which are much less than the number of original bands, significantly reduces the computational complexity.

4. CONCLUSIONS

The continuous dead pixels exist over the spectral bands represent a challenging task in the applications of HSI. There is a need to propose effective HSI inpainting methods to cope with this problem. The proposed HyInpaint makes full use of the low-rank structure of HSI and projects the high dimensional corrupted HSI to a lower dimensional subspace; then it employs a plug-and-play ADMM inpainting method to eigen-images. Both simulated data and real data experimental results show that the proposed HyInpaint method can effectively restore the dead pixels.

In addition, there is still a small part of dead pixels that are not inpainted completely. Considering that the region of continuous dead pixels is significantly large and the observed HSI was affected by noise, the error is reasonable and tolerable.

The case study on TG-1 hyperspectral VNIR data leaves some open challenges and issues for future work. Firstly, this paper mainly presents the qualitative assessments in simulated data and real data experiments. Quantitative indexes are needed to further validate the effectiveness of the proposed HyInpaint method. Field measurement for radiometric calibration is the next step work, and then it is possible to evaluate the experimental results quantitatively.

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6. REFERENCES