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Weighted Total Variation Iterative Reconstruction for Hyperspectral Pushbroom Compressive Imaging

Yingbiao Jia[1,a], Zhongliang Luo[1,b]

[1] School of Information Science and Engineering, Shaoguan University, Shaoguan, China
[a]4663776@qq.com, [b]floodflower@163.com

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Abstract: Compressed sensing is suitable for remote hyperspectral imaging, as it can simplify the architecture of the onboard sensors. To reconstruct hyperspectral image from pushbroom compressive imaging, we present iterative prediction reconstruction architecture based on total variation in this paper. As the conventional total variation prior is not effective at capturing the correlation within spatial-spectral arrays, an improved weighted total variation is proposed. Experimental results run on raw data from AVIRIS confirm the validity of the proposed method.

1. Introduction

Compressed sensing(CS)[1] is a new signal-acquisition paradigm, which shows that a sparse or compressible signal can be recovered from a relatively small number of random projections. Therefore, the acquisition presents appealing properties such as simple sampling complexity, especially in the applications of resource-constrained, such as the hyperspectral remote sensing in space-borne and air-borne earth observation.

In the hyperspectral remote sensing, the three-dimensional spatio-spectral data of a scene is created using light from different parts of the spectrum. It is costly for imaging at wavelength outside the visible light, where manufacturing detectors is very expensive. CS could be used to design cheaper sensors, or sensors providing better resolution for an equal number of detectors. So it becomes very attractive to use the CS approach to acquire hyperspectral data, which has been called hyperspectral compressive imaging. An overview of hyperspectral compressive imaging has been given [2]. The reconstruction process is an indispensable component of the hyperspectral compressive imaging as it decodes the CS measurements to render a three-dimensional spatio-spectral estimate of the scene. For a fruitful application of CS, in fact, it is necessary that the redundancy of hyperspectral images in both the spatial and spectral dimension is exploited, in a truly 3D fashion. See for example [3], where hyperspectral images are decoded from compressive samples by exploiting its spatial 2D piecewise smoothness, low-rank property and adjacent spectrum correlation. In the moving airplane and satellite platforms, compressive hyperspectral imaging need to design compressive sensor based on pushbroom and whiskbroom scanning [4].

In this paper, we consider the hyperspectral compressive pushbroom imaging and investigate suitable reconstruction algorithm. As the conventional total variation prior is not effective at capturing the correlation within spatial-spectral arrays, a weighted total variation for spatial-spectral arrays is proposed in this paper. The reconstruction relies on the minimization of weighted total variation and a progressive refinement based on prediction to jointly process the measurements of each spatial-spectral array.

2. Total variation minimization in hyperspectral CS

In image CS, two classes of convex regularizes are well known: l_1-norm and total variation (TV) norm. Compared with l_1-norm, TV regularization makes reconstructed images sharper by preserving the edges or boundaries more accurately. Total variation is defined as:

$$TV(\boldsymbol{X}) = \sum_{i,j} \sqrt{\left|(\boldsymbol{X})_{i+1,j} - (\boldsymbol{X})_{i,j}\right|^2 + \left|(\boldsymbol{X})_{i,j+1} - (\boldsymbol{X})_{i,j}\right|^2} \tag{1}$$

Since the TV is the sum of the magnitudes of the discretized gradient, seeking to minimize the TV norm relies on the assumption that the gradient is approximately sparse.

TV methods applied to HSI reconstruction have also met with success [5] and a reconstruction architecture based on total variation for compressive pushbroom imaging had been proposed [6].

3. Proposed Technique

The compressive pushbroom imaging requires separately sensed spatial-spectral arrays, so in the reconstruction, a possible solution would be applying 2D CS reconstruction to the spatial-spectral array and using another spatial dimension to refine the reconstruction. The reconstruction relies on the minimization of total variation and a progressive refinement based on linear predictors to jointly process the measurements of each spectral row, in order to exploit both spectral and spatial correlation at the same time [6]. However, conventional total variation prior is not effective at capturing the correlation within spatial-spectral arrays. As a matter of fact, the correlation in spectrum is far stronger than the correlation in space and the spatial-spectral array has different sparse degree in a different direction in the gradient domain.

The main concept behind our new reconstruction algorithm is that weighted total variation substitute for conventional total variation. As the spatial-spectral array has different sparse degree in a different direction in the gradient domain, the weighted total variation is defined as:

$$WTV(\boldsymbol{X}) = \sum_{i,j} \sqrt{\left|(\boldsymbol{X})_{i+1,j} - (\boldsymbol{X})_{i,j}\right|^2 + \lambda\left|(\boldsymbol{X})_{i,j+1} - (\boldsymbol{X})_{i,j}\right|^2} \tag{2}$$

where λ is the weight coefficient.

In order to exploit correlation among the spatial-spectral arrays, prediction/reconstruction technique is used in our algorithm. By iteratively predicting each spatial-spectral array and reconstructing the prediction error only, which is more compressible than the spatial-spectral array itself, the reconstruction will yield better results. If a prediction of the spatial-spectral array is obtained, we can cancel out the contribution of this predictor from the measurements, and reconstruct only the prediction error instead of the full spectral vector.

We represent hyperspectral images as a 3D collection of samples $\boldsymbol{X} \in R^{N_{\lambda} \times N_l \times N_p}$, where N_{λ} represents the spectral dimension and N_l and N_p represent spatial dimensions. In hyperspectral pushbroom imaging, the hyperspectral images can be considered as a collection of spatial-spectral arrays. We refer to hyperspectral images $\boldsymbol{X}$ as a $N_{\lambda} \times N_l$—N_p cube $\left[\boldsymbol{X}_1, \boldsymbol{X}_2, \cdots, \boldsymbol{X}_{N_p}\right]$, where

$\boldsymbol{X}_i \in R^{N_\lambda \times N_l} (i = 1, \cdots N_p)$.

For what concerns the acquisition of the hyperspectral pushbroom compressive imaging, it consists in the collection of the measurements for each spatial-spectral array. The measurement process of each spatial-spectral array is $\boldsymbol{Y}_i = \boldsymbol{\Phi}_i \mathrm{vec}(\boldsymbol{X}_i)$, where $\boldsymbol{Y}_i \in R^{N_m}$, and $\boldsymbol{\Phi}_i$ is of size $N_m \times N_\lambda N_l$. Here each sensing matrix $\boldsymbol{\Phi}_i$ is taken as Gaussian i.i.d. and $N_m < N_\lambda N_l$. For simplicity, the same value N_m is taken for all spatial-spectral arrays. The measurements of all spatial-spectral arrays are then collected in the matrix $\boldsymbol{Y} = \left[\boldsymbol{Y}_1, \ \boldsymbol{Y}_2, \cdots, \ \boldsymbol{Y}_{\mathrm{N_p}}\right]$.

Based on weighted total variation and prediction/reconstruction techniques, a new reconstruction algorithm for hyperspectral pushbroom compressive imaging is proposed. In the reconstruction, for every spatial-spectral array we obtain its prediction from the adjacent spatial-spectral arrays at previous iteration. For the sake of simplicity, we take the mean data of the front array and back array. The proposed iterative reconstruction algorithm is shown here:

```
Reconstruction Algorithm:
Require: Y :the matrix of CS measurements, Φ_i :the set of sensing matrix
Ensure: the estimation of X
for i = 1 to N_p do
    X^(0) ← arg min WTV(X_i)   s.t.   Φ_i vec(X_i) = Y_i
end for
n ← 0
repeat
    n ← n + 1
    for i = 1 to N_p do
        X̃_i = p(X_{i-1}^(n), X_{i+1}^(n-1))
        Ỹ_i = Φ_i X̃_i
        E_y = Y_i − Ỹ_i
        E_i ← arg min WTV(E_i)   s.t.   Φ_i vec(E) = E_y
        X_i^(n) = X_i^(n-1) + E
    end for
until Convergence is reached
return X
```

4. Experimental Results

Our simulations are mainly based on the scenes of Cuprite from AVIRIS, with 224 bands, 512 lines and 680 pixels. The corresponding hyperspectral images is cropped to have the spatial resolution 256× 256, and in addition B = 180 spectral bands is selected after discarding water absorption bands.

As a primary measure of reconstruction quality, we calculate SNR averaged over all the bands under consideration. We compare our method with three other methods: the TV algorithm separately applied on each spatial-spectral array, the weighted TV algorithm separately applied on each spatial-spectral array and the ITV method [6]. Figure 1 shows the SNR performances at different measurement rate for the test data. It can be observed that the SNR of the proposed method significantly outperforms the other two methods.

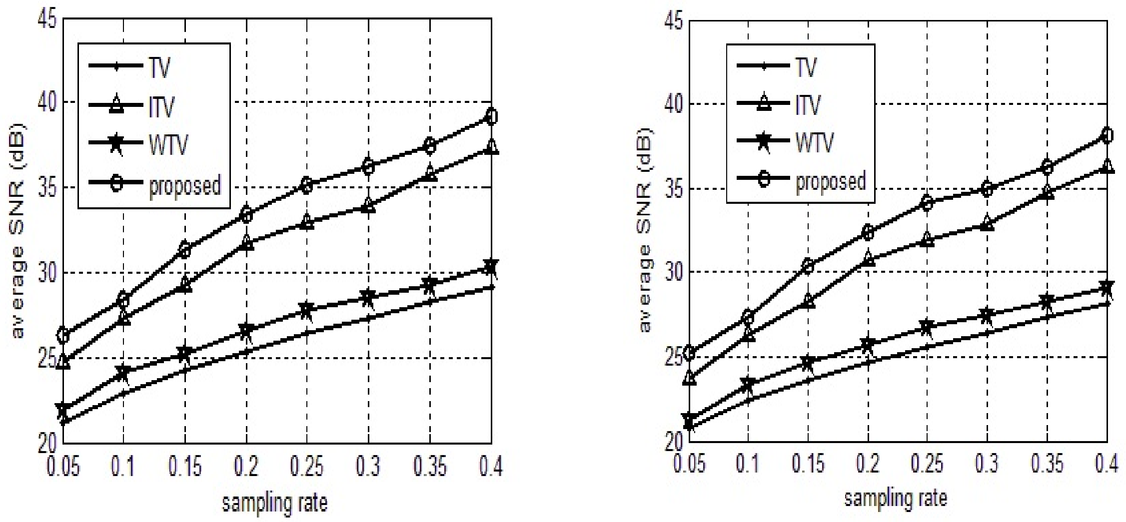

Fig. 1 Comparison of average SNR performance (left:the first scene of Cuprite from AVIRIS, right:the second scene of Cuprite from AVIRIS)

Figure 2 shows the visual quality of the reconstructed 65-th spectral band image using three different methods when sampling rate is 0.05. Obviously, our method preserves image semantics much better than the image recovered by the other two methods via recovering edges and textures more faithfully.

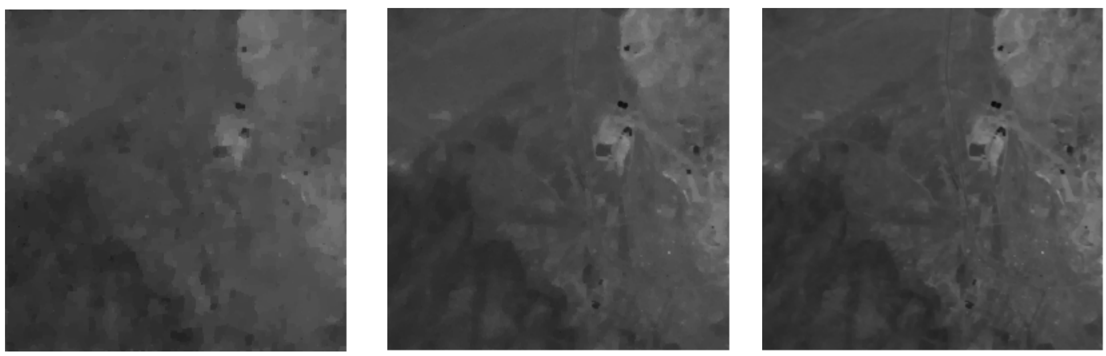

Fig. 2 The reconstructed second scene of Cuprite (left: reconstructed by TV, middle: reconstructed by ITV, right: reconstructed by the proposed method)

5. Conclusions

In this paper, we proposed an improved algorithm for the reconstruction of hyperspectral images in compressive pushbroom imaging. The reconstruction relies on the weighted total variation and a progressive refinement based on linear predictors to jointly process the measurements of each spatial-spectral array, in order to exploit both spectral and spatial correlation at the same time. Experiments run on AVIRIS images show that the number of measurements required for the HSI reconstruction is significantly reduced comparing to the other conventional methods.

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