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Three Dimensional Compressed Sensing and Reconstruction with Spectral Prediction for Hyper spectral Images

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Abstract*—An algorithm named three dimensional compressed sensing and reconstruction with spectral prediction for hyperspectral images (HSI) is proposed. The main contribution of the methodology is using spectral prediction in the reconstruction process to improve accuracy of the reconstructed images. In the framework, all bands of the hyperspectral images would be divided into groups; every group contains one reference band and some common bands. During the sampling process, the random measurements of each band are obtained using three dimensional compressed sampling (3DCS) independently. In the reconstruction process, the reference bands are reconstructed using the three dimensional total variation (3DTV). The common bands are reconstructed with the proposed reconstruct algorithm using spectral prediction. Experimental results reveal that the proposed reconstruction technique exploiting spectral correlation achieves significantly higher quality than a straightforward reconstruction that applies the 3DTV independently; compared with the existed sampling method, our sampling method 3DCS also gives a much better reconstruction result and is very efficient in the compressive of hyperspectral images.

***Index Terms*—Hyper spectral image, three dimensional compressed sampling, three dimensional total variation, bidirectional spectral prediction, reconstruction quality.**

I. INTRODUCTION

Hyper spectral imaging is a crucial technique and a powerful tool to identify and quantify distinct material substances from (often remotely) observed spectral data. It employs hyperspectral sensors to collect 2D spatial images over many contiguous spectral bands containing the visible, near-infrared, and shortwave infrared spectral bands [1].In the conventional acquisition of hyperspectral data, every element must be measured at least once in the technologies such as tunable filters or computed tomography, thus the spectral range and the spatial resolution of HSI are restricted by limitations of detector designs for data acquisition. Specially, with the spatially and spectrally resolution increasing, the volume of hyperspectral data makes transmission and analysis computationally challenging. How to manipulate HSI via a suitable compressive technique and reconstruct the images from the incomplete samples becomes critical.

Compressed sensing (CS) [2][3]theory has led to the development of imaging devices that sense at lower measurement rates than the Nyquist rate. The core idea of compressed sensing is that if a signal or image of interest is sparse or compressible in some domain, it can be reconstructed accurately from very few (relative to the dimension of the signal or image) non-adaptive measurements **Error! Reference source not found.**. CS theory provides a new research direction for hyperspectral images which satisfies the compressible condition. Hyper spectral images processing using CS for imaging [5][6], reconstruction [7][8], classification [9][10], detection [11]and unmixing [12][13]have obtained wide attention.

Hyper spectral image can be seen as a class of quasi-three-dimensional image, consists of two spatial dimensions and one spectral dimension information. The spatial image describes the spatial characteristics of two dimensional surfaces, whereas the spectral dimension reveals the spectral texture curve of each pixel. Therefore, the spatial correlation and spectral correlation exist in the hyperspectral image simultaneously; especially the spectral correlation is very strong for the high spectral resolution of the hyperspectral imaging spectrometer. In this paper, we focus on the sampling and reconstruction of hyperspectral images and explore the spectral correlation between the band images to improve the reconstruction quality.

We introduce a three dimensional compressed sampling (3DCS) method for hyperspectral imaging compression and using three dimensional total variation (3DTV) with bidirectional spectral prediction (SP) for reconstruction.

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The paper is organized as follows. Section 2 presents the overview of the proposed method, denoted as 3DCS-SP, consists of its sampling method 3DCS and the corresponding reconstruction method using spectral prediction. In this section, the scheme of the compressed sampling using 3DCS and the recovery algorithm using 3DTV is given, besides, the bidirectional spectral prediction is introduced and particularly the steps of the improved recovery algorithm are listed. The experimental results are given in Section 3 to demonstrate the performance of the proposed method followed by concluding remarks in Section 4.

II. PROPOSED ALGORITHM 3DCS-SP FOR HYPER SPECTRAL IMAGES

A. *Framework of Proposed Algorithm*

Aimed at the characteristics in hyperspectral imaging, this paper proposed the three dimensional compressed sampling (3DCS) method and the improved reconstruction algorithm using bidirectional spectral prediction (SP) to take advantage of the spectral correlation between hyperspectral bands, and the method is denoted as 3DCS-SP. The scheme of the proposed 3DCS-SP is given in Fig. 1 which describes the process of the sampling and recovery. The left rectangle is the sampling process and the right is the reconstructing process.

In the sampling process, the hyperspectral images will be divided into groups first (every group contains one reference band and some common bands), the random measurements of each band are obtained using 3DCS independently. In the reconstruction process, the reference bands are reconstructed with three dimensional total variation (3DTV) algorithm, whereas, the common bands are reconstructed with the improved reconstruction algorithm. In Fig. 1, k means the group number, $x_{k,r}$ and $x_{k+1,r}$ are the reference bands of k-th and k+1-th group, and their corresponding reconstructed bands are $\hat{x}_{k,r}$ and $\hat{x}_{k+1,r}$. The common bands in k-th group of the hyperspectral data are represented as $x_{k,2},\ldots,x_{k,j},\ldots,x_{k,p}$, where $x_{k,j}$ denotes the j-th band in the group, and their reconstructed results are $\hat{x}_{k,2},\ldots,\hat{x}_{k,j},\ldots,\hat{x}_{k,p}$.

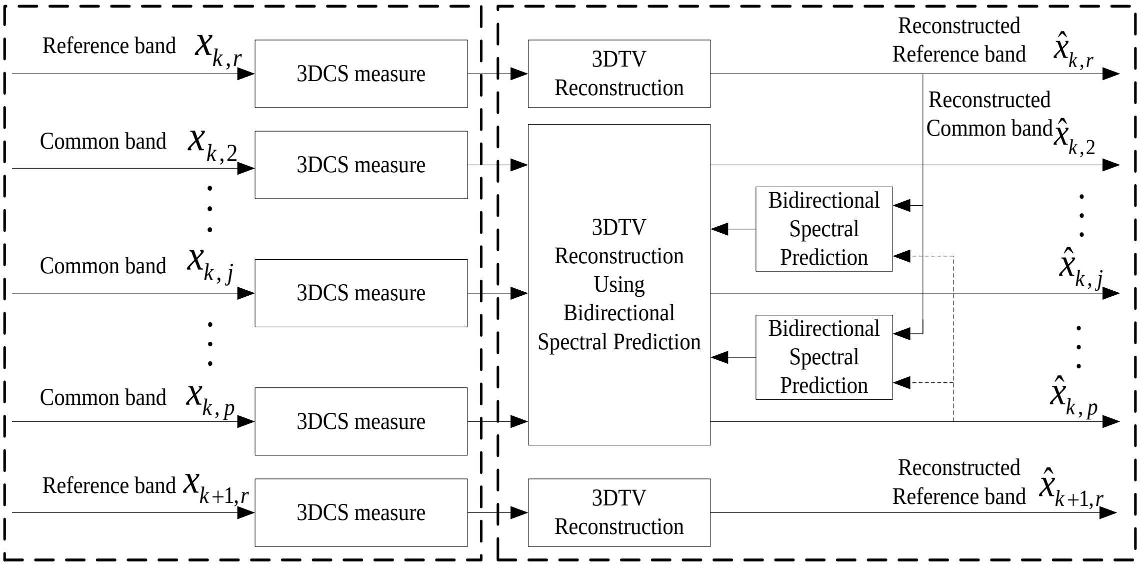

Fig. 1. The framework of proposed algorithm (3DCS-SP)

B. *Description of 3DCS and 3DTV*

Three dimensional compressed sampling and three dimensional total variation method are simply described in this section and the details can be referred to the paper [14][15]. Hyper spectral data are highly compressible with two-fold compressibility: 1) each spatial image is compressible, and 2) the entire cube, when treated as a matrix, is of low rank. To fully exploit such rich compressibility, circulant sampling [16]is introduced to replace random sampling with the advantages of fast coding and extend it from two dimensions to three dimensions. The 3D circulant sampling consists of two steps:

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(1) Random convolution. One band image $x_{k,j}$ convolves a random kernel H, denoted by $Cx_{k,j}$, where C is a circulant matrix with H as its first column. C is diagonalized as $C = F^{-1} diag(\hat{H}) F$, where $\hat{H}$ is the Fourier transform of H, denoted by $\hat{H} = FH$.

(2) Random sub sampling. It consists of random permutation (P) and band-varying sub sampling ($S_{k,j}$). $S_{k,j}$ Selects a block of M pixels from all N pixels on $PCx_{k,j}$ and obtains the sampled data $B_{k,j} = S_{k,j} PCx_{k,j}$.

For hyperspectral images, we extend the the l_1-norm based TV measure [17] $TV_{l_1}(f) = \|D_h f\|_1 + \|D_v f\|_1$ to three-dimensional (spatial and spectral) domain,

$$3DTV(x_{k,j}) = \|D_h x_{k,j}\|_1 + \|D_v x_{k,j}\|_1 + \rho \|D_\lambda x_{k,j}\|_1. \qquad (1)$$

Where, D_h and D_v are the horizontal and vertical gradient operator, D_λ is the gradient operator in the spectral dimension and ρ is proportional to the spectral correlation.

The recovery algorithm is to solve the following optimization:

$$\min_{x_{k,j}} 3DTV(x_{k,j}) \quad s.t. \quad S_{k,j} PCx_{k,j} = B_{k,j}. \qquad (2)$$

By introducing weight parameters $\alpha_h = \alpha_v = 1, \alpha_\lambda = \rho$ and auxiliary parameters $\chi = (G_h, G_v, G_\lambda, R)$, the above (2) can be rewritten as the following (3) and solved by augmented Lagrangian multipliers (ALM) [8][18] method,

$$\begin{aligned} &\min_{x_{k,j}, G_h, G_v, G_\lambda} \alpha_h \|G_h\|_1 + \alpha_v \|G_v\|_1 + \alpha_\lambda \|G_\lambda\|_1 \\ &s.t. \quad G_h = D_h x_{k,j}, G_v = D_v x_{k,j}, G_\lambda = D_\lambda x_{k,j}, R_{k,j} = Cx_{k,j}, S_{k,j} PR_{k,j} = B_{k,j} \end{aligned}. \qquad (3)$$

C. Reconstruction process

In the reconstruction process, the reference and common bands are dealed with different strategies. Firstly, the reference bands are reconstructed using 3DTV shown in (4) and (5), its corresponding reconstructed image is $\hat{x}_{k,r}$ and $\hat{x}_{k+1,r}$.

$$\min_{x_{k,r}} 3DTV(x_{k,r}) \quad s.t. \quad S_{k,r} PCx_{k,r} = B_{k,r}. \qquad (4)$$

$$\min_{x_{k+1,r}} 3DTV(x_{k+1,r}) \quad s.t. \quad S_{k+1,r} PCx_{k+1,r} = B_{k+1,r}. \qquad (5)$$

The proposed algorithm is summarized as follows: 1) obtain the predict values of the common bands using the bidirectional spectral prediction, 2) calculate the measurements of the predict values using the 3DCS sampling process, 3) calculate the difference between the measurements of the original data and the predict values, and 4) reconstruct the predict difference to revise the predict values. From Fig.1, in the k-th group, the common bands $x_{k,2}, \ldots, x_{k,j}, \ldots, x_{k,p}$ could be predicted by using $\hat{x}_{k,r}$ and $\hat{x}_{k+1,r}$ for their highly strong spectral correlation, and we define this prediction as bidirectional spectral prediction. The bidirectional predictor is:

$$x_{k,spj} = \alpha \hat{x}_{k,r} + \beta \hat{x}_{k+1,r}. \qquad (6)$$

Where, $x_{k,spj}$ is prediction of $x_{k,j}$, α and β are the coefficients,

$$\alpha = \frac{p - j + 1}{p}, \ \beta = \frac{j - 1}{p}. \qquad (7)$$

After bidirectional spectral prediction, the predict values are $x_{k,sp2}, \ldots, x_{k,spj}, \ldots, x_{k,spp}$. Then we can suppose if we use 3DCS to sample the prediction values, we can obtain,

$$y_{k,spj} = \Phi x_{k,spj}, \ j = 1, 2, \ldots., p. \qquad (8)$$

Where, Φ is the sampling matrix. Adding the prior measurement information provided by common bands $y_{k,j} = \Phi x_{k,j}, \ j = 1, 2, \ldots., p$, we compute the measurement difference between original measurement and prediction measurement:

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$$y_{k,dj} = y_{k,j} - y_{k,spj},\ j = 1, 2, ..., p. \qquad (9)$$

It is clear that $y_{k,d2},..., y_{k,dj},..., y_{k,dp}$ is the random projection of the difference $x_{k,d2},..., x_{k,dj},..., x_{k,dp}$ between the original data and the predict value; i.e.,

$$y_{k,dj} = y_{k,j} - \Phi x_{k,spj} = \Phi\left(x_{k,j} - x_{k,spj}\right) = \Phi x_{k,dj},\ j = 1, 2, ..., p. \qquad (10)$$

Because of the highly spectral correlation of hyperspectral image, the predict values are quite close to the original data, so the residual $x_{k,d2},..., x_{k,dj},..., x_{k,dp}$ should be much sparser than the original data $x_{k,2},..., x_{k,j},..., x_{k,p}$; 3DTV reconstruction should thereby be much more effective at recovering the residual $x_{k,d2},..., x_{k,dj},..., x_{k,dp}$ from $y_{k,d2},..., y_{k,dj},..., y_{k,dp}$ than it is at recovering $x_{k,2},..., x_{k,j},..., x_{k,p}$ from $y_{k,2},..., y_{k,j},..., y_{k,p}$. That is why we introduce the bidirection spectral prediction and compute the difference measurement for reconstruction.

Let $\hat{x}_{k,d2},..., \hat{x}_{k,dj},..., \hat{x}_{k,dp}$ be the recovery from $y_{k,d2},..., y_{k,dj},..., y_{k,dp}$ using 3DTV reconstruction algorithm;

$$\min_{x_{k,dj}} 3DTV\left(x_{k,dj}\right) \quad s.t. \quad S_{k,j}PCx_{k,dj} = B_{k,j},\ j = 1, 2, ..., p. \qquad (11)$$

Consequently, we can revise the prediction values $x_{k,sp2},..., x_{k,spj},..., x_{k,spp}$ and obtain the final reconstructed common bands:

$$\hat{x}_{k,j} = \hat{x}_{k,dj} + x_{k,spj},\ j = 1, 2, ..., p. \qquad (12)$$

It is conceivable that the revised prediction values taking advantage of the additional information from the reference bands and the compressed sampling measurement, which are more close to the original data than the prediction values. It should be noted that for the common bands in the last group, there is only one reference band, so we cannot obtain the predict values by bidirectional spectral prediction. In this case, the forward prediction mode is simply used, i.e., the prediction values are the reference band.

III. EXPERIMENTAL RESULTS AND ANALYSIS

Two hyperspectral data cube are used to test the performance of 3DCS-SP. The first scene is the city Changzhou supported by Shanghai Institute of Technical Physics, Chinese Academy of Sciences and the office 308 of National 863 program. The second is the cuprite scene from AVIRIS (http://aviris.jpl.nasa.gov). In the following paper, the first data cube is denoted as scene1, whereas the second cube is scene2. We choose first 64 bands of cube and intercept a sub-region (256*256) to simulate. The peak signal-to-noise (PSNR) of the reconstructed image is used to measure the performance of different reconstruction algorithms. In all experiments, the size of group is 8.

Firstly, the performance of 3DCS and proposed 3DCS-SP are compared: 1) 3DCS: The sampling method is 3DCS and the reconstruct algorithm is 3DTV. 2) 3DCS-SP: The sampling method is 3DCS, and the reconstruct algorithm is the improved algorithm using bidirectional spectral prediction. In Table I, the PSNR averaged on all bands are presented. In the experimental simulations, five sampling rate varies between 0.1 and 0.5. The data in Table I clearly states that the spectral prediction and difference reconstruction could improve the PSNR up to 3 dB. It implies that making use of spectral correlation has a great significance on improving the quality of the reconstructed image. When the sampling rate is at a low level such as 10%, the PSNR of 3DCS-SP for scene2 is still about 5dB higher than 3DCS.

We now compare the performance of our method 3DCS-SP to that of the technique in [19]named block compressed sensing with spectral prediction (BCS-SP). We compute the PSNR to evaluate the image quality and the results using three methods are shown in Fig. 2. The comparison between our 3DCS-SP and BCS-SP demonstrates that our algorithm utilizing three dimensional compressed sensing and reconstruction could get better reconstruction images. Surprisingly, the comparison between 3DCS and BCS-SP depicts that our proposed 3DCS even without spectral prediction can also achieve higher PSNR, which further proves the effectiveness of the proposed algorithm.

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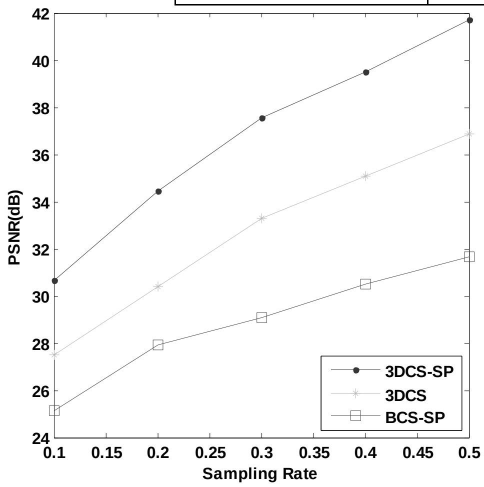
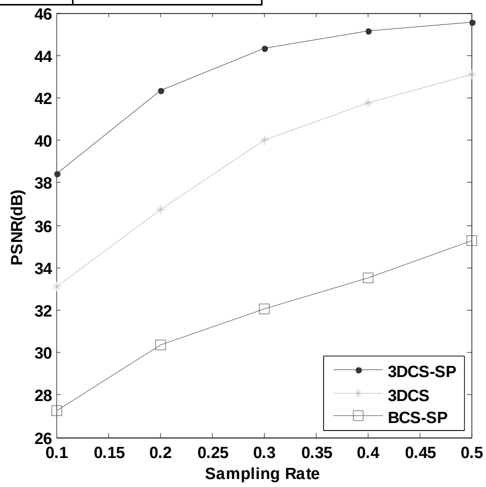
Table 1. Average PSNR in dB for two datasets

Sampling rate	3DCS	3DCS-SP
scene1		
0.1	27.5251	30.6696
0.2	30.4173	34.4591
0.3	33.2824	37.5359
0.4	35.0666	39.5232
0.5	36.8915	41.7163
scene2		
0.1	33.0980	38.4399
0.2	36.7534	42.3247
0.3	39.9956	44.3503
0.4	41.7382	45.1353
0.5	43.1294	45.5626



(a) Scene1



(b) Scene2

Fig. 2. PSNR comparison of three algorithms

Comparing the quality of the reconstructed images directly, several reconstructed images are given in Fig. 3. Without loss of generality, we only give one band (30th band of scene1) image as an example to compare the performance of different algorithms. The sampling rate is 30% and the PSNR of the reconstructed image is also given. We can find that the PSNR of the last image is the highest and the image using our proposed method is the best.

(a) (b) (c) (d)

Fig. 3. The reconstructed image of scene1 using three methods at sampling rate 30%. (a) Original image (b) reconstructed using BCS-SP, PSNR= 24.6626 dB (c) reconstructed using 3DCS, PSNR = 34.7339 (d) reconstructed using 3DCS-SP, PSNR = 40.6310 dB

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IV. CONCLUSION

In this paper, a three dimensional compressed sensing and reconstruction algorithm for hyperspectral images is proposed, which takes advantage of spectral correlation to improve the quality of the reconstructed image. The hyperspectral images would be divided into groups first and the bands are grouped into reference bands or common bands. The characteristic of the reconstruct algorithm is using bidirectional spectral prediction to enhance the sparsity of the difference between the original measurement and prediction measurement. Experimental results demonstrate that our proposed method 3DCS-SP has a great superiority on improving the performance of the reconstruction images. After bidirectional spectral prediction, the PSNR of the reconstructed image of our method 3DCS-SP is higher than 3DCS, and with the decreasing of the sampling rate, the superiority is more obviously. Finally, using the same spectral prediction on our method 3DCS and existed method BCS, the results reveal that our sampling method is very efficient in the compressive of hyperspectral images and gives higher quality reconstructed images.

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