Block Compressive Sampling and Wiener Curvelet Denoising Approach for Satellite Images

R. Monika, A. Anilet Bala and A. Suvarnamma

Abstract Satellite optical system produces high-resolution images which deal with large volume of data. This imposes strain on embedded resources which require more memory and computing capacity. In classical satellite imaging system, conventional compression algorithms like JPEG were used. However, they are not very efficient in reducing the data rate. In order to overcome this, block compressive sensing (BCS) technique, reweighted sampling (RWS) are used. This technique provides block-by-block sampling continuously at a rate which is very much less than the Nyquist rate. Due to the interference with high frequency signal in the environment, noise is induced in the compressed data from the satellite while transmitting them to the ground station. Curvelet transform with Wiener filtering technique (CTWF) is used for significant denoising of the BCS data. Experimental results show that BCS along with denoising technique reproduces images with better PSNR values.

Keywords Block compressive sensing · Reweighted sampling
Curvelet transform · Wiener filtering · OMP · Sparse binary random matrix

1 Introduction

Satellite image processing has been the focus of work in recent years. With the advancement in satellite imaging systems, the resolution of the image captured is very high. Transmitting or storing such a high-resolution image becomes a serious problem because of the energy and bandwidth constraints. In order to overcome

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these problems, compression of data is essential. Conventional compression techniques are not so efficient for satellite image applications.

Compressed sensing (CS) is an effective alternative, which performs compression at a rate lesser than Nyquist sampling rate [1]. But CS cannot be applied for real-time sensing of images, as the entire image is sampled at a time. Therefore, BCS is used in which the entire image is divided into small blocks [2] and CS is applied to each block independently. Since same measurement matrix is used memory requirement is less. Blocks are processed independently; therefore, the initial solution can be easily obtained and reconstruction process is speeded up.

Compressed images from the satellite are more prone to noise, which can degrade the quality of the image. It is essential to remove the noise and to improve the image quality. Image denoising can be considered as recovering a signal from inaccurately measured samples which is partially accomplished by CS. However in order to remove the noise added in the environment, denoising methods are essential. Many transform-based denoising techniques like Fourier, wavelet, ridgelets are available. However, most of them have certain shortcomings in terms of image quality and computational efficiency. In order to achieve better PSNR, CTWF technique is used.

In this paper, combination of both BCS and CTWF technique is used to retain good quality image with low data rate.

2 Related Works

Donoho [3] explained that signals or images can be recovered from fewer measurements or samples than the one described in Nyquist sampling theorem. In CS, sampling and compression are performed simultaneously to speed up the process. He suggested that CS can be applied to the signals only if it is compressible and sparse.

Gan [4] discussed the acquisition of images in block-by-block manner. This technique is simpler and efficient than normal compressed sensing technique and can effectively capture complicated structures of the image. Same measurement matrix is applied to all the blocks. Therefore, this technique requires less storage space.

Yang et al. [5] introduced a new weighting process into the conventional CS framework. Weight values are calculated for all frequency components. Signal components with larger magnitude will have large weight value and can be reconstructed more precisely. As a result, enhanced reconstructed image quality can be obtained.

Starck et al. [6] describe about the implementation of Curvelet transform for denoising. Images are reconstructed with low computational complexity. Curvelet reconstruction offers higher quality recovery of edges thereby improving the perceptual quality when compared to that of wavelet-based image reconstructions.

Ansari et al. [7] compared denoising techniques using wavelet, curvelet and contourlet transforms for remote-sensed images with additive Gaussian noise. The Curvelet-based denoising technique preserves the sharpness of the boundaries. The geometrical structure of the image can be effectively captured by the curvelets.

The rest of the paper is organized as follows: overview of compressed sensing is provided in Sects. 3 and 4 discusses about the satellite image processing system, experimental results are provided in Sects. 5 and 6 concludes the paper.

3 Overview of CS

Let x denotes a real-time finite length signal to be acquired. As per the hypothesis of CS, there exists a basis ψ where s is sparse up to sufficient level. s can be row or column vector. The equation is given by

$$x = \psi s \tag{1}$$

This means there exist k non-zero elements such that $k \ll n$. ψ can be any transform like discrete cosine transform or discrete wavelet transform. Let the matrix y represents a set of m linear combinations of x. These linear combinations can be represented as matrix ϕ with size $m \times n$ and are called measurements. The CS is represented as

$$y = \phi x = \phi \psi s \tag{2}$$

The measurements matrix ϕ used in this paper is sparse binary random matrix. This matrix has only binary values 0 and 1's, and it satisfies restricted isometry property (RIP). If the measurement matrix used satisfies RIP [3], then the length of all sufficiently sparse vectors are approximately preserved under transformation by the matrix. The other measurement matrices generally used are Gaussian matrix, Bernoulli random matrix and Sub-Gaussian random matrices. Orthogonal matching pursuit (OMP) is used as reconstruction algorithm [8].

4 Satellite Image Processing System

Figure 1 shows the block diagram of satellite image processing system. The satellite imaging system captures the image of the target. The images are high-resolution images. In order to store or process such a large volume of data, more energy will be consumed by the processor. To reduce the amount of data, BCS technique is used. This compressed data is then transmitted to the ground station. Noises in the environment get added to the data. To remove the noise, CTWF technique is used. The various techniques used are described briefly in this section.

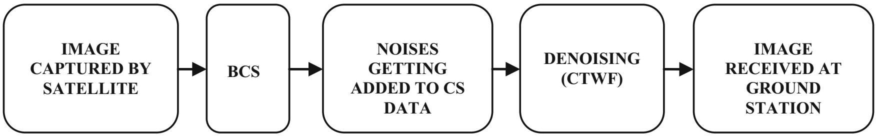

Fig. 1 General block diagram of satellite image processing system

4.1 Block Compressed Sensing

BCS adopts an adaptive projection representation, i.e. direction of projection is along the direction where the signal components have larger magnitude. As a result, it can efficiently capture the geometric structures of natural images. Also the computational complexity is reduced as same measurement operator is applied to all the blocks and can be easily stored. Each block is processed independently; therefore, the reconstruction process is speeded up. In this paper BCS technique, RWS is used.

(A) *Reweighted sampling* [5]

Reweighted Compressive Sampling for image compression introduces a weighting process to extract low-frequency components of the image. Weight values are assigned for all frequency components. Low-frequency components have large weight values. Therefore, this scheme shows discrimination to various components of the image. RWS sampling is given by the following equation,

$$y = \phi\psi Ws \tag{3}$$

where W is a diagonal weighting matrix with weighting coefficients $\{w_1, w_2, \ldots w_n\}$ corresponding to different frequency component. Weight is calculated as sum of the mean and square root of variance of DC coefficients. By introducing the weighting matrix, the signal components with large magnitudes are effectively captured, which improves recovery precision.

4.2 Denoising

Noises in image degrade the quality of the image. The conventional spatial filtering technique reduces noise, but the edges of the images are blurred. Here, Curvelet transform along with Wiener filtering technique overcomes this disadvantage.

(A) *Curvelet transform* [6]

In Curvelets, multiscale ridgelets transform is combined with a spatial bandpass filtering to isolate different scale. Curvelets occur at all scales, locations, and orientations, but they have varying widths and length. Hence, they have variable anisotropy, whereas ridgelets have only global length and variable widths. Therefore, curvelets are used in this paper.

One of the important advantages of using Curvelet transform is that it analyses the image with different block sizes using a single transform. Initially the image is decomposed into a set of wavelet bands, and then ridgelet transform is applied to each band. The block size can be changed at each scale level.

(B) *Wiener filtering*

Compare to all other filtering technique, the most commonly used is Wiener filter. This is because only a few computational steps are required for execution and are very fast to process. Linear equations are used to calculate the filter weight which reduces the noise level of the signal. Curvelet transform itself provides better denoising. In order to increase the PSNR values, Wiener filtering is combined with Curvelet transform.

5 Experimental Results

Matlab R2012a is used for software simulation. The test images are taken by satellite available in image database [9]. In the BCS technique, block size of 8×8 is chosen. Number of pixel values chosen from each block is only 10 out of 64.

Table 1 shows the PSNR values obtained for various images using BCS technique. The number of pixel values chosen from each block is only 10 out of 64.

Table 1 PSNR values for various images

Technique = BCS number of measurements = 10	
Image	PSNR
Mountain image	24.2312
Airport image	25.9982

Table 2 PSNR values for various noise levels (mountain image)

Sigma value (noise in dB)	CTWF PSNR (dB)	Wiener filter PSNR (dB)
10	26.6820	26.7325
20	25.5570	25.2649
30	24.3212	23.5304
40	23.1547	21.9023
50	22.0576	20.4918

Table 3 PSNR values for various noise levels (airport image)

Sigma value (noise in dB)	CTWF PSNR (dB)	Wiener filter PSNR (dB)
10	28.4436	28.2892
20	26.9750	26.4231
30	25.3600	24.2592
40	24.0161	22.4060
50	22.7080	20.8062

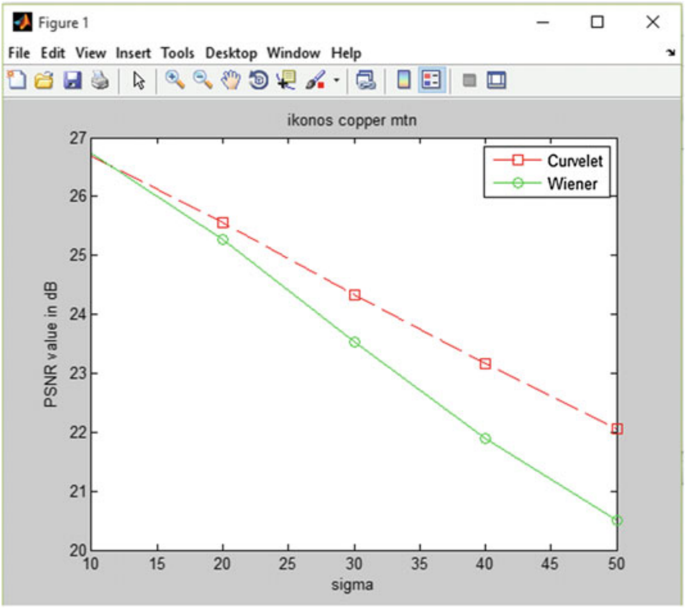

Fig. 2 Graphical representation of sigma versus PSNR

Additive White Gaussian noise is added to the BCS data by using Matlab inbuilt function. Now in order to remove the noise, denoising technique CTWF is used. The PSNR value comparison for mountain and airport images at various amounts of noise levels varying from $\sigma = 10$ to 50 dB is shown in Tables 2 and 3.

It can be seen from the table that CTWF has achieved better PSNR values than normal Wiener filtering for various noise levels. If noise level is high, then CTWF is the most efficient technique in achieving better image quality. In order to check the consistency of the technique, it is tested with various satellite images. Table 3 shows the PSNR value comparison for airport image at various noise levels as considered before.

The graphical representation of various noise levels and their corresponding PSNR values is shown below. The graph is plotted for mountain image (Fig. 2).

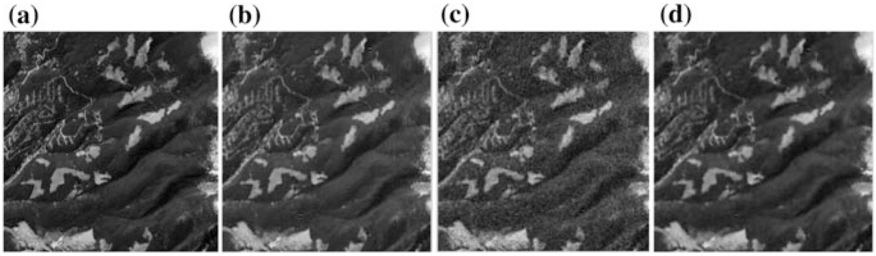

Fig. 3 **a** Original Ikonos image **b** BCS compressed image **c** noisy image **d** denoised using CTWF

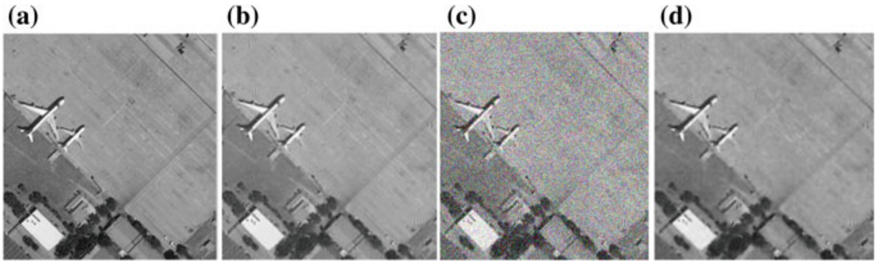

Fig. 4 **a** Original airport image **b** BCS compressed image **c** noisy image **d** denoised using CTWF

It can be seen from the graph that as the noise level increases, both CTWF and Wiener filtering have decrease in PSNR values. But however CTWF has improved PSNR values than normal Wiener filtering as the noise level increases. Hence CTWF is considered to be the best denoising technique in achieving good PSNR values.

Visual quality comparison is shown below. The quality of images after applying both techniques is found to be good with better PSNR values. Figure 3a shows the original Ikono's mountain image taken from the database available in [9]. Figure 3b–d, show the image after applying BCS, noise, CTWF, respectively. Similiarly, Fig. 4a shows the original airport image taken from the database available in [9]. Figure 4b–d show the image after applying BCS, noise, CTWF, respectively.

Visual quality comparison shows that even with lesser number of measurements, BCS is very efficient in reconstructing the image. Also CTWF also helps in significant noise removal and gives better PSNR values when compared to that of normal Wiener filtering. Hence BCS with CTWF is considered to be the most efficient method in achieving good quality images with better PSNR values.

6 Conclusion and Future Work

Image reconstruction using BCS and denoising using CTWF for satellite images is investigated in this paper. BCS can effectively reconstruct images with fewer measurement values. Noise in the BCS data can be effectively removed by using CTWF technique. The final image obtained by applying BCS–CTWF is found to have better PSNR values with good image quality.

The future work is to adopt a technique which gives significant improvement in the reconstructed image quality.

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