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Directional Remote Sensing

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ABSTRACT. Concepts of directional remote sensing are put forward based on two-dimensional compressive sensing. Very little measured data are required to acquire and reconstruct change areas in directional remote sensing. The measured data in one-dimensional compressive sensing not only keep the energy of a sparse signal, but also inherit the sparse signal's direction information. However, direction information can't be applied to reconstruction and test of a sparse signal in one-dimensional compression sensing. The two-dimensional compressive sensing model is proposed based on sparse features of change areas in remote sensing. Moreover, a sparse signal reconstruction algorithm (two-step reconstruction method, 2SRM) is proposed based on two-dimensional compressive sensing by use of the energy and direction information. The theoretical analysis and experimental results show the signal reconstruction ability of 2SRM is stronger. SNR (Signal to Noise Ratio) and PSNR (Peak Signal to Noise Ratio) of 2SRM increase by 16.57 dB as compared with a single traditional reconstruction algorithm at most.

Keywords: directional remote sensing, change detection, two-dimensional compressive sensing (2DCS), structure prior information, two-step reconstruction method (2SRM).

1. Introduction

It's very difficult to sample change area data directionally because of uncertainty and unpredictability of them. Conventional data collecting of entire zone leads to repeat work of no change areas so that capital and resource are wasted (Li 2011).

According to the conventional Shannon's sampling theorem, the sampling rate should be more than twice the Nyquist sampling rate. Compressive sensing can surpass the limits of sampling theory. The sampling rate is much lower than that needed in Shannon's sampling theorem by exploring the compressibility or the sparsity of the signal. (1) is the compressive sensing model. If the signal $\mathbf{x}$ is sparse, it can be recovered accurately by (1):

$$\min \left\|\mathbf{x}\right\|_0 \; s.t. \; \mathbf{y} = \mathbf{\Phi x} \, , \tag{1}$$

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where $\mathbf{x} = (x_1, \cdots, x_N)^T$, $\mathbf{x} \in R^N$; l_0 norm of $\mathbf{x}$ is $\|\mathbf{x}\|_0$, which is simply the number of non-zero elements in $\mathbf{x}$; $\mathbf{y}$ is the measured data, $\mathbf{y} \in R^M$; $\mathbf{\Phi}$ is a measurement matrix, $\mathbf{\Phi} \in \mathrm{R}^{M \times N}$, $M < N$; $\min \|\mathbf{x}\|_0$ is objective function; $\mathbf{y} = \mathbf{\Phi x}$ is constraint function.

Change areas of remote sensing images are generally very sparse. Hence, compressive sensing can be used for change detection by virtue of the sparsity hypothesis of change areas. The difference between remote sensing images in different temporal phases is the change area in an ideal condition (Cevher et al. 2008).

2. Two-dimensional compressive sensing

Natural images and change areas have good prior information such as spatio-temporal continuity, structure, gradient and correlation. Adjacent columns of an image are similar, although grey values change considerably in different zones. Energies of adjacent column vectors are close and their correlation coefficients are close to 1 (Cheng 2014). If prior information is used fully, the accuracy and efficiency of sparse signal reconstruction can be improved and enhanced.

However, current compressive sensing are one-dimensional (Cheng et al. 2013). The signal $\mathbf{x}$ and the measured data $\mathbf{y}$ are one-dimensional, too. A two-dimensional signal like an image has to be transformed into a one-dimensional signal in one-dimensional compressive sensing. Thus structure priori information of images is destroyed. Hence prior information of a two-dimensional signal can barely be used in one-dimensional compressive sensing. Only the minimum total variation method (TV) uses the gradient information of an image in its objective function (Rong et al. 2011).

Push broom imaging by a linear array of detectors is main data collection technology in remote sensing. Hence prior information of images is retained when natural images are collected based on linear array push-broom mode. Set the length of a scanning strip equal to L. If the matrix $\mathbf{X}$ ($\mathbf{X} \in R^{N \times L}$) represents a scanning strip, the scan line of a satellite or an aircraft can only acquire a column of $\mathbf{X}$ once. The compressive sensing model of remote sensing is represented in (2):

$$\min \|\mathbf{x}_j\|_0 \quad \text{s.t.} \quad \mathbf{Y} = \mathbf{\Phi X}, \quad j \in [1, L], \tag{2}$$

where $\mathbf{Y} \in R^{M \times L}$, $\mathbf{x}_j$ is a column vector of $\mathbf{X}$, $\mathbf{y}_j$ is a column vector of $\mathbf{Y}$.

Although remote sensing images $\mathbf{X}_{t1}$ in temporal t1 and $\mathbf{X}_{t2}$ in temporal t2 are not sparse, change areas $\Delta\mathbf{X}$ is sparse, $\Delta\mathbf{X} = \mathbf{X}_{t2} - \mathbf{X}_{t1}$. The remote sensing image $\mathbf{x}_{jt1}$ in temporal t1 is acquired by traditional methods; the measured data $\mathbf{y}_{jt1}$ in temporal t1 and $\mathbf{y}_{jt2}$ in temporal t2 are acquired by the compressive sensing method. $\Delta\mathbf{x}_j$ can be reconstructed by (1), $\Delta\mathbf{y}_j = \mathbf{y}_{jt2} - \mathbf{y}_{jt1}$. Then $\mathbf{X}_{t2} = \mathbf{X}_{t1} + \Delta\mathbf{X}$.

It has been demonstrated that change area can be reconstructed losslessly by 2 times as much as its data based on the difference of unlike temporal CS measurement values (Duarte-Carvajalino and Sapiro 2009). The amount of measured data based on compressive sensing is almost equal to the amount of the acquired data of directional remote sensing based on known change areas. Therefore, the remote sensing and change detection method is called directional remote sensing in this paper.

3. Feature analysis of measured data ΔY, change area ΔX, reconstruction result ΔX_R and corresponding transform domain coefficient ΔC and ΔC_R based on two-dimensional compressed sensing

Fig. 1 is the difference image of Sardinia island between September 1995 and July 1996. The remote sensing image represents flooded area around Mulargia Lake of Sardinia Island in Italy in July 1996 (International Scientific Data Service Platform 2015). Grey values of black zones are zero in Fig. 1. It's. The image is $\Delta\mathbf{X}$, and its size is 256×351.

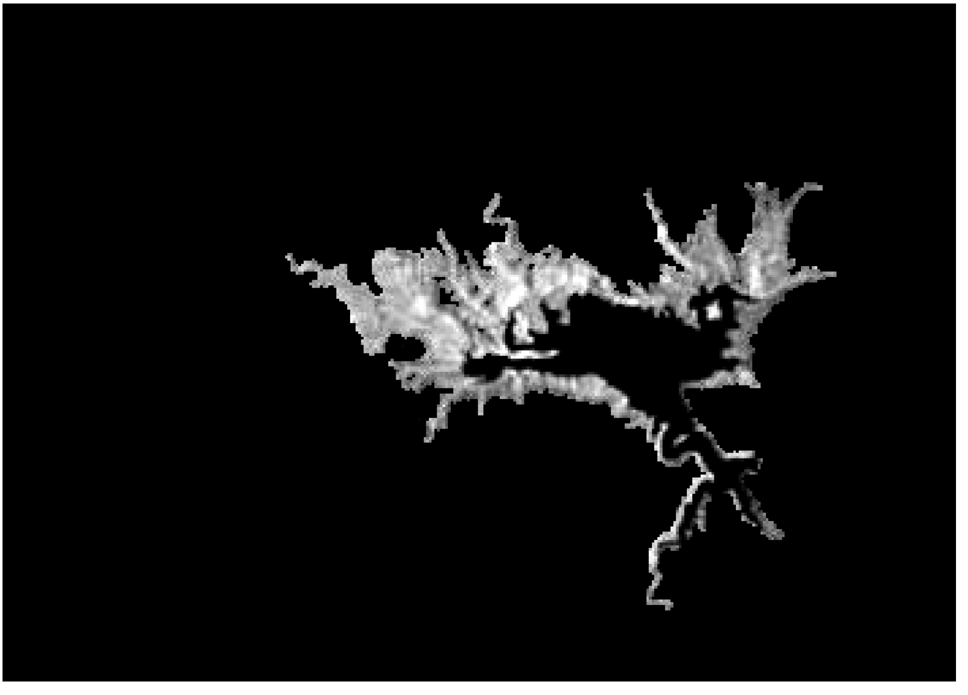

Fig. 1. *Difference image of Sardinia island between September 1995 and July 1996.*

Gaussian measurement matrix $\mathbf{\Phi}$ in this paper is used, $\mathbf{\Phi} \in R^{128\times256}$. Every column $\Delta\mathbf{x}_j$ of $\Delta\mathbf{X}$ is reconstructed by OMP [Orthogonal Matching Pursuit (Donoho et al. 2012)] column by column. $\Delta\mathbf{X}_R$ is the reconstructed result, as shown in Fig. 2.

The x axis of Fig. 2 and Fig. 3 represents the column number j ($j \in [1,351]$) of the gray image $\Delta\mathbf{X}$ in Fig. 1. $\Delta\mathbf{X}$ is a matrix in nature, too. In mathematics, physics and engineering, a vector has length and direction. A vector is frequently represented by a line segment with a definite direction, or graphically as an arrow, connecting an initial point (the origin of a Euclidean space) with a terminal point. The length of the vector is the distance between the two points, i.e. the norm of the vector. And the direction refers to the direction of displacement from the initial point to the terminal point (Heinbockel 2001). In signal fields, energy is a concept widely used, i.e., square of norm of a vector.

The curves in Fig. 2 (a) represent the energy of every column of $\Delta\mathbf{Y}$, $\Delta\mathbf{X}$ and $\Delta\mathbf{X}_R$, and are called energy curves in this paper. The energy of every column of $\Delta\mathbf{Y}$, $\Delta\mathbf{X}$ and $\Delta\mathbf{X}_R$ in Fig. 2 (a) are normalized in order to contrast with Fig. 2 (b), i.e. all columns are divided by $\|\Delta\mathbf{y}_{max}\|_2$. $\|\Delta\mathbf{y}_{max}\|_2$ is the maximum of all $\|\Delta\mathbf{y}_j\|_2$. The curves in Fig. 2 (b) represent the correlation coefficient μ of adjacent columns of $\Delta\mathbf{Y}$, $\Delta\mathbf{X}$ and $\Delta\mathbf{X}_R$, i.e. the cosine of the included angle between two directions of adjacent column vectors. And the curves of Fig. 2 (b) are called direction curves in this paper. Fig. 2 (c) is the reconstructed gray image of the change area. Zoom processing of Fig. 2 (c) is done in order that the length of Fig 2 (a), (b) and (c) is same.

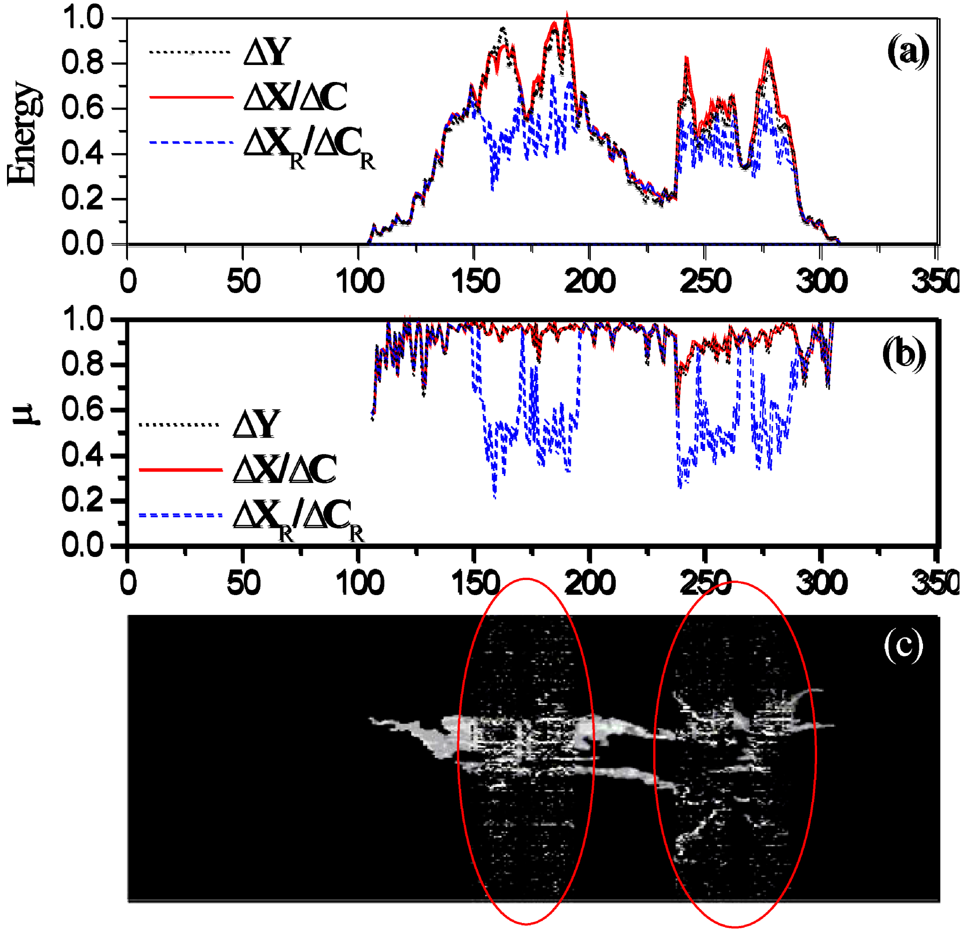

Fig. 2. *Analysis curves of ΔX, ΔC, ΔX_R, ΔC_R and ΔY and gray image. (a) Energy; (b) Correlation coefficient between 2 columns; (c) Reconstructed difference image by OMP+null.*

3.1. Energy feature analysis of ΔX and ΔY

The curves $\Delta\mathbf{X}$ and $\Delta\mathbf{Y}$ in Fig. 2 (a) are similar because the Gaussian matrix has good Restricted isometry property (RIP) and good universality. RIP is shown in (3). Therefore, the reconstruction effect of $\Delta\mathbf{X}_{\mathrm{R}}$ can be judged by use of the energy curve analysis of $\Delta\mathbf{Y}$ and $\Delta\mathbf{X}_{\mathrm{R}}$:

$$(1-\sigma_K)\,\|\mathbf{x}\|^2 \le \lambda_{\min}(\mathbf{\Phi}_I^T\mathbf{\Phi}_I)\,\|\mathbf{x}\|^2 \le \|\mathbf{\Phi}\mathbf{x}\|^2 = \|\mathbf{\Phi}_I\mathbf{x}_I\|^2 \le \lambda_{\max}(\mathbf{\Phi}_I^T\mathbf{\Phi}_I)\,\|\mathbf{x}\|^2 \le (1+\sigma_K)\,\|\mathbf{x}\|^2, \quad (3)$$

where $\lambda_{\min}(\mathbf{\Phi}_I^T\mathbf{\Phi}_I)$ and $\lambda_{\max}(\mathbf{\Phi}_I^T\mathbf{\Phi}_I)$ denote the minimal and maximal eigenvalues of $\mathbf{\Phi}_I^{\mathrm{T}}\mathbf{\Phi}_I$, respectively (Candes and Tao 2005, Dai and Milenkovic 2009). $\mathbf{\Phi}_I$ consists of the columns of $\mathbf{\Phi}$ with indices $j \in I$; And $\mathbf{x}_I$ is composed of the entries of $\mathbf{x}$ indexed by $j \in I$. $I \subset \{1,\ldots,N\}$. $\sigma_K \in [0,1)$.

3.2. Direction feature analysis of ΔX and ΔY

Energy and direction are two basic properties of a vector. Direction information can be measured well by the correlation coefficient μ between adjacent columns according to RCP (Restricted Conformal Property) (Cheng 2014). Measurements can retain approximately not only energies but also directions of signals in compressive sensing because of RIP and RCP. Gaussian matrix has good Restricted Conformal Property. Two curves $\Delta\mathbf{X}$ and $\Delta\mathbf{Y}$ in Fig 2 (b) are almost same. Fig. 2 (b) shows that $\Delta\mathbf{Y}$ completely inherits the direction information of $\Delta\mathbf{X}$. Therefore, the reconstruction effect of $\Delta\mathbf{X}_{\mathbf{R}}$ can be scaled by use of the correlation analysis between $\Delta\mathbf{Y}$ and $\Delta\mathbf{X}_{\mathbf{R}}$.

3.3. Energy and direction features analysis of ΔX$_R$

The curves $\Delta\mathbf{X}_{\mathrm{R}}$ in Fig. 2 (a) and (b) are the experimental results using OMP to reconstruct $\Delta\mathbf{X}$. After checking, those zones of the curves $\Delta\mathbf{X}_{\mathrm{R}}$ and $\Delta\mathbf{X}$ outside the overlaps are those columns which were reconstructed unsuccessfully. The partial curves $\Delta\mathbf{X}_{\mathbf{R}}$ and $\Delta\mathbf{X}$ which are outside the overlaps match badly. Zones outside the overlaps in Fig. 2 (b) are more easily recognizable than Fig. 2 (a). The direction curve $\Delta\mathbf{Y}$ is more suitable for testing the reconstruction effect of $\Delta\mathbf{X}_{\mathbf{R}}$ than the energy curve $\Delta\mathbf{Y}$ in Fig. 2 based on RCP, RIP and the experimental results.

3.4. Energy and direction features analysis of ΔC and ΔC$_R$

The curves $\Delta\mathbf{C}$ and $\Delta\mathbf{X}$ are same completely in Fig. 2 and Fig. 3, $\Delta\mathbf{C}_{\mathbf{R}}$ and $\Delta\mathbf{X}_{\mathbf{R}}$ completely overlap, where $\Delta\mathbf{X} = \mathbf{\Psi}\Delta\mathbf{C}$ and $\Delta\mathbf{X}_R = \mathbf{\Psi}\Delta\mathbf{C}_R$. The sparse transform base $\mathbf{\Psi}$ in Fig. 2 and Fig. 3 is discrete cosine transform (DCT). $\mathbf{\Psi}$ is an orthogonal matrix. The orthogonal matrix can preserve the length and direction (i.e. the angle between two vectors) of a vector, $\|\Delta\mathbf{x}_j\|_2 = \|\Delta\mathbf{c}_j\|_2$ and $\dfrac{\langle\Delta\mathbf{x}_j,\Delta\mathbf{x}_{j+1}\rangle}{\|\Delta\mathbf{x}_j\|_2\cdot\|\Delta\mathbf{x}_{j+1}\|_2} = \dfrac{\langle\Delta\mathbf{c}_j,\Delta\mathbf{c}_{j+1}\rangle}{\|\Delta\mathbf{c}_j\|_2\cdot\|\Delta\mathbf{c}_{j+1}\|_2}$, where $\|\Delta\mathbf{x}_j\|_2$ represents energy of the jth column of $\Delta\mathbf{X}$, i.e. 2-norm, $\dfrac{\langle\Delta\mathbf{x}_j,\Delta\mathbf{x}_{j+1}\rangle}{\|\Delta\mathbf{x}_j\|_2\cdot\|\Delta\mathbf{x}_{j+1}\|_2}$ represents the cosine of the angle between the jth column and the $(j+1)$th column of $\Delta\mathbf{X}$, i.e. the correlation coefficient μ.

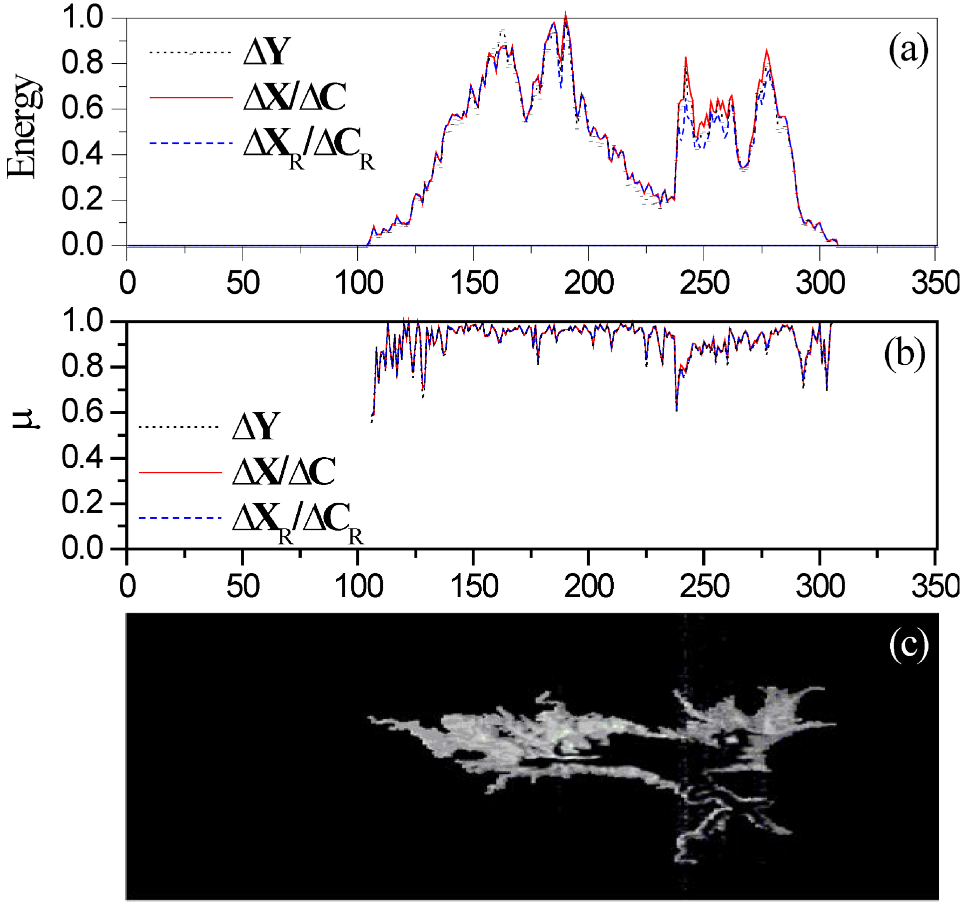

Fig. 3. *Analysis curves of ΔX, ΔC, ΔX_R, ΔC_R and ΔY and gray image. (a) Energy; (b) Correlation coefficient between 2 columns; (c) Reconstructed difference image by OMP+TV.*

4. Reconstruction algorithms of the change area based on two-dimensional compressive sensing

To facilitate the presentation, the zones outside overlaps of the curves of $\Delta \mathbf{X}_\mathbf{R}$ and $\Delta \mathbf{X}$ are called uncertain areas, otherwise certain areas.

4.1. Combinations of reconstruction algorithms in certain areas and uncertain areas

If a signal is sparse enough, the reconstruction effect of l_0 algorithms [for example OMP, Stagewise orthogonal matching pursuit (StOMP (Donoho et al. 2012)), Subspace pursuit (SP (Dai and Milenkovic 2009)) and Compressive sampling matching pursuit (CoSaMP (Needell and Tropp 2009)) etc.] is better than l_1 algorithms [for example Basis Pursuit (BP), interior point method, iterative threshold method and gradient projection (GPSR) etc.] and TV algorithm. l_0 algorithms are more suitable to certain areas and can accurately reconstruct certain areas. Although the reconstruction ability of StOMP, SP and CoSaMP is better than OMP, the signal's sparse must be known in advance. It is almost impossible in practice. Hence OMP is used to reconstruct certain areas in this paper.

The sparse is high in uncertain areas. Uncertain areas can be regarded as compressible signals. Good reconstruction effect can be obtained by use of l_0 or l_1 algorithm after transforming uncertain areas by DCT or Discrete Fourier Transform (DFT). The reconstruction matrix is $\mathbf{\Phi\Psi}'$ now. Both DFT and DCT are widely used. But DFT contains complex numbers and the complex numbers is not easy to display in images. Therefore, DCT is used in this paper.

Although interior point method, iterative threshold method and GPSR are faster than BP, BP has the better reconstruction ability. Hence BP is used in this paper. TV algorithm can use the gray gradient to get better reconstruction effect for compressible signals than l_0 and l_1 algorithms. And it's unnecessary to do sparse transformation in TV. Therefore, TV is suitable for compressible signals.

In order to compare reconstruction results of different combinations based on reconstruction algorithms, the combinations of reconstruction algorithms in certain areas and uncertain areas in this paper include OMP+null, OMP+OMP, OMP+BP, TV+null and OMP+TV. That on the left of "+" is the reconstruction algorithm adopted by certain areas while that on the right of "+" is the reconstruction algorithm adopted by uncertain areas. "Null" means that the same reconstruction algorithm which is on the left of "+" is adopted in certain areas and uncertain areas.

4.2. The criteria to distinguish certain areas and perfect reconstruction of a signal

Places where the curves $\Delta\mathbf{X}_R$ and $\Delta\mathbf{Y}$ do not tally in Fig. 2 (a) and (b) are uncertain areas. As shown in Fig. 2 (a) and (b), the deviation between direction curves $\Delta\mathbf{X}_R$ and $\Delta\mathbf{Y}$ in Fig. 2 (b) is clearer and larger than the corresponding energy curves $\Delta\mathbf{X}_R$ and $\Delta\mathbf{Y}$ in Fig. 2 (a). Hence the deviation of direction curves can be taken regard as the criteria to discriminate certain areas and uncertain areas. $|\mu_{\Delta\mathbf{x}_j} - \mu_{\Delta\mathbf{y}_j}| / \mu_{\Delta\mathbf{y}_j} < 9\%$ in certain areas of Fig. 2 (b).

$\mathbf{\Phi}_I$ of uncertain areas is bigger so that its RIP is good. $|\mu_{\Delta\mathbf{x}_j} - \mu_{\Delta\mathbf{y}_j}| / \mu_{\Delta\mathbf{y}_j} < 5\%$ in uncertain areas of Fig. 2 (b). 7% between 5% and 9% is an empirical value after a lot of experiments. 7% is taken as the threshold value whether the sparse signal was reconstructed successfully in this paper. If the empirical value is larger, too many certain areas would be misjudged as uncertain areas. If the empirical value is smaller, too many uncertain areas would be misjudged as certain areas.

4.3. Two step reconstruction method for 2D Compressive Sensing

According to the above idea, the two-dimensional compressive sensing reconstruction algorithm is put forward, i.e. two step reconstruction method for 2D Compressive Sensing (2SRM). First of all, reconstruct every column $\Delta\mathbf{x}_j$ of the two-dimensional sparse signal $\Delta\mathbf{X}$ based on $\min\|\Delta\mathbf{x}_j\|_0$ s.t. $\Delta\mathbf{y}_j=\mathbf{\Phi}\Delta\mathbf{x}_j$ column by column by OMP (or other l_0 reconstruction algorithms), and obtain $\Delta\mathbf{X}_\mathrm{R}$. Secondly, divide columns of $\Delta\mathbf{X}_\mathrm{R}$ into certain areas and uncertain areas according to $|\mu_{\Delta\mathbf{x}_j}-\mu_{\Delta\mathbf{y}_j}|/\mu_{\Delta\mathbf{y}_j}<7\%$; Thirdly, reconstruct $\Delta\mathbf{c}_j$ column by column by use of OMP (or other l_1 reconstruction algorithms) based on $\min\|\mathbf{c}_j\|_0$ s.t. $\Delta\mathbf{y}_j=\mathbf{\Phi\Psi}'\Delta\mathbf{c}_j$ or by use of BP (or other l_0 reconstruction algorithms) based on $\min\|\mathbf{c}_j\|_1$ s.t. $\Delta\mathbf{y}_j=\mathbf{\Phi\Psi}'\Delta\mathbf{c}_j$. Then calculate $\Delta\mathbf{x}_{Rj}=\mathbf{\Psi}\Delta\mathbf{c}_{Rj}$ to obtain $\Delta\mathbf{X}_\mathrm{R}$. Or reconstruct every column $\Delta\mathbf{x}_j$ of the two-dimensional sparse signal $\Delta\mathbf{X}$ based on $\min\|\Delta\mathbf{x}_j\|_{TV}$ s.t. $\Delta\mathbf{y}_j=\mathbf{\Phi}\Delta\mathbf{x}_j$ column by column by TV to obtain $\Delta\mathbf{X}_\mathrm{R}$. The specific steps are shown in algorithm 1.

Algorithm 1 (2SRM)

Input: $\mathbf{\Phi}$, $\Delta\mathbf{Y}$

Step 1:

1) Reconstruct $\Delta\mathbf{x}_j$ of $\Delta\mathbf{X}$ column by column by use of OMP (or other l_0 algorithms) based on $\min\|\Delta\mathbf{x}_j\|_0$ s.t. $\Delta\mathbf{y}_j=\mathbf{\Phi}\Delta\mathbf{x}_j$.
2) If $|\mu_{\Delta\mathbf{x}_{Rj}}-\mu_{\Delta\mathbf{y}_j}|/\mu_{\Delta\mathbf{y}_j}>7\%$ between neighbor columns of $\Delta\mathbf{X}_\mathrm{R}$ and $\Delta\mathbf{Y}$, these columns belong to uncertain areas, otherwise on the contrary.

Step 2:

Initialization: $J=\{j$ indices corresponding to those columns of indeterminate areas of $\Delta\mathbf{X}\}$, $j_{\max}$ corresponding to the last column of $\Delta\mathbf{Y}$ or $\Delta\mathbf{X}$.

Iteration: At the jth iteration, go through the following steps.

1) If $j\in\mathbf{J}$, reconstruct $\Delta\mathbf{c}_j$ column by column by use of OMP (or other l_0 algorithms) based on $\min\|\mathbf{c}_j\|_0$ s.t. $\Delta\mathbf{y}_j=\mathbf{\Phi\Psi}'\Delta\mathbf{c}_j$ or by use of BP (or other l_1 algorithms) based on $\min\|\Delta\mathbf{c}_j\|_1$ s.t. $\Delta\mathbf{y}_j=\mathbf{\Phi\Psi}'\Delta\mathbf{c}_j$ and set $\Delta\mathbf{x}_{Rj}=\mathbf{\Psi}\Delta\mathbf{c}_{Rj}$; Or reconstruct $\Delta\mathbf{x}_j$ column by column by use of TV based on $\min\|\Delta\mathbf{x}_j\|_{TV}$ s.t. $\Delta\mathbf{y}_j=\mathbf{\Phi}\Delta\mathbf{x}_j$.
2) If $j=j_{\max}$, quit the iteration.

Output: The reconstructed signal $\Delta\mathbf{X}_\mathrm{R}$.

4.4. Experimental results analysis of 2SRM

NR and PSNR of five 2SRM such as OMP+null, OMP+OMP, OMP+BP, TV+null and OMP+TV are shown in Table 1. SNR and PSNR of OMP+TV increase by 16.57 dB compared to OMP+null. Those zones in the two ellipses of Fig. 2 (c) are very vague, while those corresponding zones of Fig. 3 (c) are clear. The curves $\Delta\mathbf{X}_\mathrm{R}$

and $\Delta\mathbf{X}$ of the former match poorly in Fig. 2 (a) and (b), the curves $\Delta\mathbf{X}_R$ and $\Delta\mathbf{X}$ of the latter are almost identical in Fig. 3 (a) and (b).

SNR and PSNR of OMP+OMP decrease by 2.5292 dB as compared with OMP+BP, while OMP+OMP increases by 6.5379 dB as compared with OMP+null. Because OMP can completely reconstruct certain areas, so SNR and PSNR of OMP+TV increased by about 1.7353 dB as compared with TV+null. The reason that the improvement of OMP+TV is more than TV+null lies in certain areas. OMP can reconstruct completely certain areas, while TV can't do. Although the amount of columns in certain areas is much more than in uncertain areas, the energy in certain areas is much less than in uncertain areas. OMP+TV is the best combination of all combinations in Table 1. Reconstruction ability of TV is very strong in reconstructing the direction information of a signal, as shown in Fig. 3 (b). The direction curve $\Delta\mathbf{X}_R$ tallies well with $\Delta\mathbf{X}$ in Fig. 3 (b), while the energy curve $\Delta\mathbf{X}_R$ tallies badly in Fig. 3 (a). The reconstruction effect can be improved if the curve $\Delta\mathbf{X}_R$ in uncertain areas is normalized by $\Delta\mathbf{x}_{Rj}=\frac{\Delta\mathbf{x}_{Rj}}{\|\Delta\mathbf{x}_{Rj}\|_2}\cdot\|\Delta\mathbf{y}_j\|_2$ in OMP+TV. However, the improvement of SNR and PSNR is little. It is only 0.002 dB. In a real remote sensing imaginary and on a large scale, change areas are very sparse, i.e. certain areas are much more. Hence SNR and PSNR of Table 1 would be much higher.

Table 1. *SNR and PSNR of 2SRM with different combinations.*

	OMP+null	**OMP+OMP**	**OMP+BP**	**TV+null**	**OMP+TV**
SNR (dB)	1.5293	8.0672	10.5964	16.3632	18.0985
PSNR (dB)	17.0691	23.6070	26.1362	31.9031	33.6383

5. Conclusions

The theory and method of directional remote sensing based on two-dimensional compressive sensing are proposed. Directional remote sensing can acquire and reconstruct change areas by 2-3 times measured data. Meanwhile, the two-dimensional compressive sensing model is put forward. It can keep the two-dimensional structure priori information of remote sensing images. And it is suitable for the linear array push-broom mode of remote sensing. Moreover, 2SRM based on two-dimension compressive sensing is put forward. It can use the energy and direction information of measured data and signals to reconstruct change areas of remote sensing. Reconstruction ability of 2SRM is better than that of OMP, BP and TV etc. SNR and PSNR of OMP+OMP increase by 6.54 dB as compared with OMP+null. SNR and PSNR of OMP+TV increase by 1.74 dB as compared with TV+null. SNR and PSNR of OMP+BP increase by 9.07 dB as compared with OMP+null. SNR and PSNR of OMP+TV increase by 16.57 dB as compared with OMP+null.

6. Future works

In order to simplify the research object, change detection is only studied under the ideal condition. However, real change detection and real remote sensing are related to noise/error, radiation correction, geometric correction and other issues. The difference image of remote sensing images in different temporal is not absolutely sparse, too. How to further consider the introduction of more practical factors is an important work for us to carry out the follow-up in order that the experimental analysis is closer to the real situation.

The empirical value 7% which is suitable for OMP and 128×256 Gaussian measurement matrix are adopted in this paper. How to determine the quantitative indices according to more experimental and theoretical analysis is also the follow-up work.

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Usmjereno daljinsko istraživanje

SAŽETAK. Koncepti usmjerenog daljinskog istraživanja postavljeni su na osnovi dvodimenzionalnog kompresivnog istraživanja. Potrebno je vrlo malo mjernih podataka da bi se postigla i rekonstruirala područja promjena u usmjerenom daljinskom istraživanju. Mjerni podaci u jednodimenzionalnom kompresivnom istraživanju ne samo da čuvaju energiju rasutih signala već, također, preuzimaju informacije o smjeru rasutog signala. Informacija o smjeru se ipak ne može primijeniti za rekonstrukciju i ispitivanje rasutog signala u jednodimenzionalnom kompresivnom istraživanju. Model dvodimenzionalnog kompresivnog istraživanja predlaže se na osnovi rasutih svojstava područja promjene u daljinskom istraživanju. Osim toga, algoritam rekonstrukcije rasutog signala (metoda rekonstrukcije u dva koraka, 2SRM) predlaže se na osnovi dvodimenzionalnog kompresivnog istraživanja koristeći informacije o energiji i smjeru. Teorijska analiza i eksperimentalni rezultati pokazuju da je sposobnost rekonstrukcije signala primjenom metode 2SRM jača. SNR (vrijednost omjera signala i šuma) i PSNR (vrijednost maksimalnog omjera signala i šuma) primjenom metode 2SRM povećavaju se najviše za 16,57 dB u odnosu na pojedinačni tradicionalni algoritam rekonstrukcije.

Ključne riječi: *usmjereno daljinsko istraživanje, otkrivanje promjene, dvodimenzionalno kompresivno istraživanje (2DCS), struktura prije informacije, metoda rekonstrukcije u dva koraka (2SRM).*

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