Research on Compression Perceptual Hyperspectral Image Reconstruction Based on GISMT

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Abstract. Hyperspectral images contain rich information, including diversity of space, radiation and spectrum information. However, the huge amount of information also causes the problem of large amount of hyperspectral image data, which makes the hyperspectral image data face a lot of problems in the aspects of transmission and storage. To solve this problem, a compression sensing hyperspectral image reconstruction algorithm based on GISMT is proposed. This paper first introduces the improved joint sparse representation model, and then, based on the improved joint sparse representation model, designs a joint sparse representation solution algorithm based on GISA, GISMT, simulation results table. This method can improve the reconstruction effect of hyperspectral remote sensing image.

Introduction

In 2006, a new theoretical framework, compression perception (Compressive Sensing, CS) theory, was developed. In less than ten years, the Shannon-Nyquist sampling theorem was continuously perfected, and each of its research results could bring about revolutionary progress in the field of signal processing. Has the broad development prospect and the application space. Its core point is that assuming the signal can be represented by sparsity, as long as the signal is sparse or compressible, the low-dimensional observation signal can restore and reconstruct the high-dimensional original signal well, which brings a new direction to large-scale image sampling and processing.

Although some achievements have been made in the study of the theory of compressed perception, there are still many problems that need to be studied and discussed in depth. Can we find a more sparse representation model to deal with the signal representation to meet the premise of sparse signal processing, so as to achieve a sufficient number of observations; Second, can we find an optimal orthogonal observation matrix for different reconstruction algorithms; third, find an optimal algorithm with low computational complexity to solve the NP difficult signal convex optimization problem, and quickly realize the reconstruction signal. Fourth, in the practical application of how to better The theory of compressed perception is combined with practical problems to solve practical problems. It has the following characteristics:

First, the data amount is large, the information contained is much, but the data is redundant, and the correlation between the adjacent bands is high;

Second, narrow band; the spectral interval between each band is generally less than or equal to 10nm;

Third, high spectral resolution; There are only a few bands in IM, SPOT, and the width of bands is mostly 100-200nm. They all get images from several discrete bands. The hyperspectral band width is nanoscale, which can be used for continuous spectral imaging of the target. The influence of other interference factors is greatly restrained in spectral space. The absorption characteristic width of many ground objects is generally 20-40 nm, so hyperspectral remote sensing images can meet the general requirements of ground object detection and accurately detect non-detectable substances in wide band remote sensing, which is conducive to the fine recognition of ground objects.
Basic Description of 2 GISMT Algorithm

Improved Joint Sparse Representation Model

Suppose a N-dimensional signal $x \in \mathbb{R}^N$, then the transformation coefficient vector of $x$ in $\Psi$ domain can be expressed as $\Psi T_x$. If there are only $K$ nonzero elements ($N \gg K$) or only $K$ large components in the transform coefficient $\Psi$, then the signal $x$ is considered to be $K$ sparse or approximate $K$ sparse. Suppose there is a random projection $M \times N$ dimension ($M < N$) measurement matrix $A$, the linear projection of signal $x$ results in the $M$ dimension measurement value $y$, which is expressed as $y = Ax$. The mathematical expression is as follows: (1) constrained optimization problem:

$$
\min_x \| \Psi x \|_p \quad s.t. \quad y = Ax
$$

(1)

Where $p$ takes a value of 1 or 0, $\| \cdot \|_0$ represents the sum of the absolute values of all elements in a vector; Represents $\| \cdot \|_0$, representing the number of non-zero elements in a vector.

Image priori knowledge plays a key role in the performance of image reconstruction algorithm. Remote sensing images themselves have two basic prior knowledge characteristics, namely, local smoothness and non-local self-similarity. The improved joint sparse representation model of remote sensing images is as follows:

$$
\Psi_{\text{cos}}(x) = \tau \cdot \| \Psi_{L2D}x \|_p + \lambda \cdot \| \Psi_{N3D}x \|_p
$$

(2)

In the formula, $\lambda$ denotes the regularization constraint term and tradeoff the sparsity of two prior knowledge.

Specifically, $\| \Psi_{L2D}x \|_p$ Corresponding to the prior knowledge of local smoothness, the local continuity of image is maintained and the noise is effectively suppressed. The mathematical expression is as follows:

$$
\| \Psi_{L2D}x \|_p = \| D x \|_p = \| D_v x \|_p + \| D_h x \|_p
$$

(3)

Where $D$ is a gradient operator and $D_v, D_h$ is a horizontal and vertical gradient operator.

The global self-similarity of nonlocal 3D transform domain is described by combining the coefficient sparsity of all 3D groups of image blocks. The mathematical expression is as follows:

$$
\| \Psi_{N3D}x \|_p = \| \Theta_x \|_p = \sum_{i=1}^{\frac{N}{3}} \| T^{3D}(Z_i) \|_p
$$

(4)

A column vector representing all transform coefficients of an image $x$. Refer to the literature for a more detailed mathematical description.

Consider the following constrained optimization problems:

$$
\min_x \frac{1}{2} \| y - Ax \|_2^2 + \lambda \| x \|_p
$$

(5)

In the formula, $\lambda$ nonnegative regularization parameter. Wangmeng Zuo et al are inspired by soft threshold and iterative contraction threshold method IST. A generalized iterative contraction algorithm (General Iterated Shrinkage Algorithm, is proposed. GISA) is used to solve a class of non-convex Lp norm sparse minimization problems. The general threshold function GST is as follows.

$$
T_p^{GST}(y; \lambda) = \begin{cases} 
0 & \text{if } |y| \leq \tau_p^{GST}(\lambda) \\
\text{sgn}(y) \cdot S_p^{GST}(|y|; \lambda) & \text{if } |y| > \tau_p^{GST}(\lambda)
\end{cases}
$$

(6)
A gradient descent process based on A or y is involved in each iteration, with a common contraction / threshold as follows:

$$x^{(k+1)} = T_p^{\text{GST}} \left( x^k - \|A\|^2 A^T (Ax - y); \|A\|^2 \lambda \right)$$  \hspace{1cm} (7)

**Improved Joint Sparse Representation Model Optimization Algorithm Based on GISA**

The improved joint sparse representation model (2), (3), (4) is replaced by the original representation (1). On the basis of reducing the image sampling rate and preserving the original image features, two inherent sparseness of remote sensing images are described. The objective function of remote sensing image reconstruction based on compressed sensing and sparsity is obtained as follows:

$$\min_x \tau \cdot \|Dx\|_p + \lambda \cdot \|\Theta_u\|_p \text{ s.t. } y = Ax$$  \hspace{1cm} (8)

Based on the regularization idea, the auxiliary variable Dx=d, x=u, is introduced to transform the constrained optimization problem of the formula (3-8) into the unconstrained optimization problem of the following formula (9).

$$\min_{x,d,u} \frac{1}{2} \|Ax - y\|^2 + \alpha \cdot \|x-u\|^2 + \frac{\eta}{2} \|Dx - d\|^2 + \tau \cdot \|d\|_p + \lambda \cdot \|\Theta_u\|_p$$  \hspace{1cm} (9)

The regular term α, η→∞, formula (8) and formula (9) have the same solution and are solved by alternating minimization method.

(1) x subproblem

Given du, x can be solved from the following formula

$$\min_x \frac{1}{2} \|Ax - y\|^2 + \alpha \cdot \|x-u\|^2 + \frac{\eta}{2} \|Dx - d\|^2$$  \hspace{1cm} (10)

The approximate solution of x is obtained by (10):

$$x = F^{-1} \left( \frac{F(\eta D^T d) + F(A) \cdot F(y)}{\eta (F(D^T D_u) + F(A) \cdot F(A))} \right)$$  \hspace{1cm} (11)

Where F is a two-dimensional Fourier transform, F-1 is a two-dimensional Fourier inverse transformation, * is a conjugate complex number, Multiplies for a particular component.

(2) u subproblem

Given DX, u can be solved from the following formula:

$$\min_u \frac{\alpha}{2} \|x-u\|^2 + \lambda \cdot \|\Theta_u\|_p$$  \hspace{1cm} (12)

Considering r as the observed value of a certain type of noise of x, the expression (12) can be equivalent to:

$$\min_u \frac{1}{2} \|u-r\|^2 + \frac{\lambda}{\alpha} \sum_{i=1}^n \|T^3D(Z_{u_i})\|_p$$  \hspace{1cm} (13)

Based on the above assumption, the u, r∈RN, Θ_u, Θ_r∈RK, according to the theorem of large numbers, there are two equations for the existence of the maximum probability of the coefficient vector of three-dimensional transformation in each iteration as follows:
\[ \frac{1}{N} \| u^{(k)} - r^{(k)} \|_2^2 = \sigma^2, \quad \frac{1}{K} \| \Theta_u^{(k)} - \Theta_r^{(k)} \|_2^2 = \sigma^2 \]  
(12)

To merge (14) into (13) to obtain

\[ u = \min_{\nu} \frac{1}{2} \| \Theta_u - \Theta_r \|_2^2 + \frac{K}{N\alpha} \| \Theta_u \|_p \]  
(15)

According to the GST function, the approximate solution for each iteration of \( u_i \) is:

\[ u_i = T_{p}^{\text{GST}} \left( \Theta_i, K \frac{\lambda}{N\alpha} \right) \]  
(16)

(3) subproblem d

Given UX, and defining \( d_{\text{ref}} = Dx \), d:

\[ \min_{\tau} \frac{\eta}{2} \| d - d_{\text{ref}} \|_2^2 + \tau \| d \|_p \]  
(17)

Using the GST function, the approximate solution for each iteration of \( d_i \) is:

\[ d_i = T_{p}^{\text{GST}} \left( d_{\text{ref}}^{(i)}; \tau / \eta \right) \]  
(18)

To sum up, the flow chart of the algorithm is shown in figure 1.

![Flow chart of remote sensing image reconstruction algorithm based on GISA.](image)

To sum up, we analyze (8) the optimal algorithm of GISA remote sensing image reconstruction model based on compression perception and sparsity.
Experimental Results and Analysis

Experimental Results

The hyperspectral data of HJ-1A star are used in the experiment. The hyperspectral remote sensing data of HIS class 2 product in Daxinganling region of Heilongjiang Province are used as the data source in this paper. In this paper, the hyperspectral remote sensing image numbered L1A0002851779 is selected for experiment. There are 115 spectral bands in this image.

![Figure 2. (a) Reconstruction effect of original Image (b) MT-Bayes algorithm Reconstruction effect of (c) GPSR algorithm Reconstruction effect of (d) algorithm in this paper.](image)

In this paper, the reconstruction effect of the 50th band is shown in figure 6, where (a) is the original image, (b) is the MT-Bayes algorithm reconstruction effect, (c) is the GPSR algorithm reconstruction effect, (d) is the algorithm reconstruction effect in this paper. It can be seen from figure (6) that the reconstruction effect of multidirectional prediction between spectra is much better than that of the first two algorithms in the reconstruction of non-reference images.

Analysis of Experimental Results

In this paper, we select a band group to calculate the PSNR value, in which 50 band is the reference image, the MT-Bayes algorithm, the GPSR algorithm and the PSNR result of the proposed algorithm are shown in Table 1.

![Table 1. Average PSNR comparison of different average sampling rates.](image)

As can be seen from Table 1, compared with the GPSR algorithm and the MT-Bayes algorithm, the proposed compression sensing hyperspectral image reconstruction method based on GISMT and the average PSNR of the reference image prediction method improved 4-5dB at different average sampling rates. It can be seen that the reconstruction effect of the proposed algorithm at different sampling rates has been significantly improved.

Conclusion

In this chapter, the process of improving the joint sparse representation model is described in detail in this chapter. The 2D base and the 3D base are constructed by two basic prior knowledge of the remote sensing image, and the two regularized parameters are adjusted to balance the overall sparsity of the remote sensing image. In order to solve this improved model, the basic theoretical knowledge of the GISA algorithm is introduced, and a compression-aware remote sensing image reconstruction algorithm based on GISA is proposed, and the effectiveness of the reconstruction algorithm is verified by programming and simulation experiments. Compared with the common algorithm, the method has the advantages of high feasibility, good experimental effect and high reconstruction rate, and provides a new thinking for the reconstruction of the high-spectrum image.
References


