Study on super - resolution reconstruction algorithm based on sparse representation and dictionary learning for remote sensing image

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Abstract—**Super-resolution image reconstruction plays a very important role in the interpretation of remote sensing images. Especially when the resolution of images is low, the size of the objects to be identified is close to the minimum resolution, and can be reconstructed by super-resolution better interpretation of the feature. In this paper, K-SVD algorithm is used to study the exampler of high resolution image library, and the dictionary of high resolution remote sensing image is obtained. The low resolution image is represented by high resolution dictionary, and the remote sensing reconstruction of remote sensing image is realized. Which improves the peak noise ratio and mean square error of the image, and has better performance than the interpolation algorithm. The method proposed in this paper has important significance and application prospect in remote sensing image application.**

Keywords- Super-resolution; exampler; K-SVD; Sparse Representation

I. INTRODUCTION

The resolution of remote sensing image is a measure of the resolution of the details of the output image by the remote sensing imaging system, and it is also an indicator of the degree of detail of the geomorphic information in the remote sensing image [1, 2]. At present, the resolution of the definition of different focus, there are a variety of resolution representation, such as remote sensing image spatial resolution, remote sensing image temporal resolution [3], remote sensing image spectral resolution, remote sensing image radiation resolution, etc., which remote sensing image Spatial resolution is the size of the smallest target object that the telemetry sensor can distinguish [4, 5].

The main purpose of the super-resolution remote sensing image reconstruction is to reconstruct the high-resolution (HR) remote sensing image by the signal processing technology based on the single or multiple low-resolution (LR) remote sensing images. Super-resolution image reconstruction plays a very important role in the interpretation of remote sensing images. Especially when the resolution of images is low, the size of the objects to be identified is close to the minimum resolution, and can be reconstructed by super-resolution better interpretation of the feature [6]. The resolution of remote sensing image is dependent on the expensive sensor equipment and the complicated image processing algorithm. Because the cost of satellite transmission is very high, it is difficult to improve the resolution of the sensor in the remote sensing platform once the transmission is successful. To solve this problem, Tsai and Huang proposed a high-resolution reconstruction method in the frequency domain with multiple low-resolution images in 1984 to fuse the complementary pixels of the pixels of multiple images in a pair of images [7].

At present, the super-resolution reconstruction method based on remote sensing image can be divided into two kinds, the first is based on the parameter method, the output image is reconstructed by the edge parameter information model, and the other method is based on the model, The internal source finds an instance of the corresponding block and then fills the missing pixel [8]. Each method has advantages and disadvantages, and the parameter-based method achieves the overall reasonable output effect by constructing the "general" edge information. Instance-based methods are often noised and require a lot of time overhead.

The super-resolution reconstruction method of remote sensing image based on sparse representation and dictionary learning is a super-resolution reconstruction as a inverse process of remote sensing image obtaining. By modeling the sparse representation of single or multiple remote sensing images, the recovery of high-resolution remote sensing images is achieved, thus obtaining higher peak signal-to-noise ratio (PSNR) and visual effects. Based on this theory, a series of high resolution remote sensing image super-reconstruction (SR) of post-processing methods have been proposed in recent years. In 2004, J. Núñez et al. proposed a method of super-reconstruction by additional wavelet algorithm. The method of wavelet decomposition is used to reconstruct the remote sensing images based on a series of unsampled remote sensing images [9]. In 2009, LiWei et al. proposed a method based on Hidden Markov tree, which normalized the ill-posed problem in a wavelet domain through a priori model, and realized the remote sensing reconstruction of the remote sensing image [10].

Because the remote sensing image acquired by the ground is produced by a series of high-resolution remote sensing

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images through a series of descending processes, it is a pathological problem to obtain the ideal high-resolution remote sensing image according to the degraded observation remote sensing image. Low resolution remote sensing image reconstruction (Super resolution, SR) is a hot topic in the field of remote sensing image research. In this section, we use the K-SVD algorithm to study the high-resolution remote sensing image library by using the K-SVD algorithm to obtain a dictionary that can sparse representation the high-resolution remote sensing image. Super resolution of remote sensing image has been achieved through feature extraction, independent component analysis and reconstruction of high-resolution remote sensing images. Through experiment, this method improves the peak noise ratio of image and has better performance than other super-resolution reconstruction algorithms.

II. SUPER - RESOLUTION REMOTE SENSING IMAGE RECONSTRUCTION MODEL BASED ON SPARE REPRESENTATION

A. The Principle of Super - distance Image Reconstruction Based on Sparse Representation

Based on the theory of compressed sensing, low-resolution remote sensing image blocks can be viewed as samples of high-resolution images. When high-resolution image blocks can be viewed by non-correlation measurement matrices by linearly combining elements in a dictionary, the high-resolution remote sensing image can be accurately restored by its low-resolution block. Based on this theoretical basis, the super - resolution algorithm based on case block and the self-learning remote sensing image algorithm are proposed. Low-resolution remote sensing images are viewed as high-resolution remote sensing images formed by down-sampling, blur and noise, etc., expressed as:

$$\mathbf{I}_{LR} = \mathbf{S}\mathbf{H}\mathbf{I}_{HR} + \mathbf{v} \tag{1}$$

Where $\mathbf{S}$ denotes the sampling of the image, $\mathbf{H}$ denotes the blur of the image, $\mathbf{I}_{HR}$ denotes the high-resolution remote sensing image, $\mathbf{v}$ denotes the noise, and the purpose of the super - resolution reconstruction is to reconstruct the high-resolution image from the obtained low-resolution image, but also by sampling, the quantitative process can be digitized, and in the image sampling process due to sensor displacement, transmission process noise interference can also cause image degradation. In addition, remote sensing image post-correction will cause image degradation. The recovery of high-resolution images from acquired low-resolution images is an NP-hard problem. The reconstruction of high-resolution remote sensing images depends on the following three aspects:

1. The obtained low resolution images;
2. The prior knowledge and the statistical properties of noise;
3. The prior of remote sensing image.

According to the characteristics of remote sensing images, as well as the work of Elad [12] and Yang [11], this paper proposes a low-resolution image block of any given size $p\times p(p\in Z^+)$, with the column vector $\mathbf{I}_{LR}\in R^m$, $m=p^2$. The goal of the super-resolution reconstruction is to reconstruct its high-resolution image form $q\times q(q\in Z^+)$, $\mathbf{I}_{HR}\in R^n, n=q^2$, which can be expressed as a representation by a linear measurement and measurement matrix $\mathbf{H}$,which is:

$$\mathbf{I}_{LR}=\mathbf{H}\cdot\mathbf{I}_{HR}, \mathbf{H}\in R^{m\times n} \tag{2}$$

$\mathbf{I}_{LR}$ is the subsampling form of $\mathbf{I}_{HR}$, according to the literature [13,14], where $p=2$, $q=4$, H is a given matrix, its magnification is: $q\ /\ p$.

B. The dictionary learning algorithm based on exampler block

According to the characteristics of remote sensing image, the high resolution remote sensing image block set is defined as: $\mathbf{X}_h=\{\mathbf{x}_1,\mathbf{x}_2,\ldots\mathbf{x}_Q\}$, $\mathbf{x}_i\in R^{q\times q}$, and assuming that the image blocks can be obtained by linear combination of atoms in the dictionary $\mathbf{D}_h=[\mathbf{d}_1,\ldots\mathbf{d}_K]\in R^{n\times K}$, and each $\|\mathbf{d}_j\|_2=1$, $j=1,\ldots K$, expressed as:

$$\mathbf{x}_i=\mathbf{D}_h\boldsymbol{\beta}_i, \boldsymbol{\beta}_i\in R^K, \|\boldsymbol{\beta}_i\|_0 << K \tag{3}$$

Where $\boldsymbol{\beta}=[\boldsymbol{\beta}_1,\boldsymbol{\beta}_2,\ldots,\boldsymbol{\beta}_Q]$, the goal of dictionary learning is to minimize the reconstruction error in an image block set, ie:

$$\min\|\mathbf{X}_h-\mathbf{D}_h\boldsymbol{\beta}\|_2^2,\ \text{s. t}.\|\boldsymbol{\beta}_i\|_0\le K,\ \ i=1,2,\ldots Q \tag{4}$$

According to KSVD dictionary learning algorithm, the solution of the problem can be divided into two steps:

Step 1: Sparse coding. Fixed dictionary $\mathbf{D}_h$, solved the sparse coefficient .of image block $\mathbf{X}_h$

Step 2: Dictionary updates. Update each atom (atom in the dictionary), and sparse representation of each image block $\boldsymbol{\beta}$.

The specific process can be expressed as:

1) Initializing dictionary $\mathbf{D}_h$ as a DCT dictionary.

2) According to the KSVD dictionary learning algorithm, calculate the maximum singular value and the relevant singular vector, update the dictionary $\mathbf{d}_j=\mathbf{u}_1$, $\beta^k=\sum_{1,1}\mathbf{v}_1$, and obtain he dictionary $\mathbf{D}_h$.

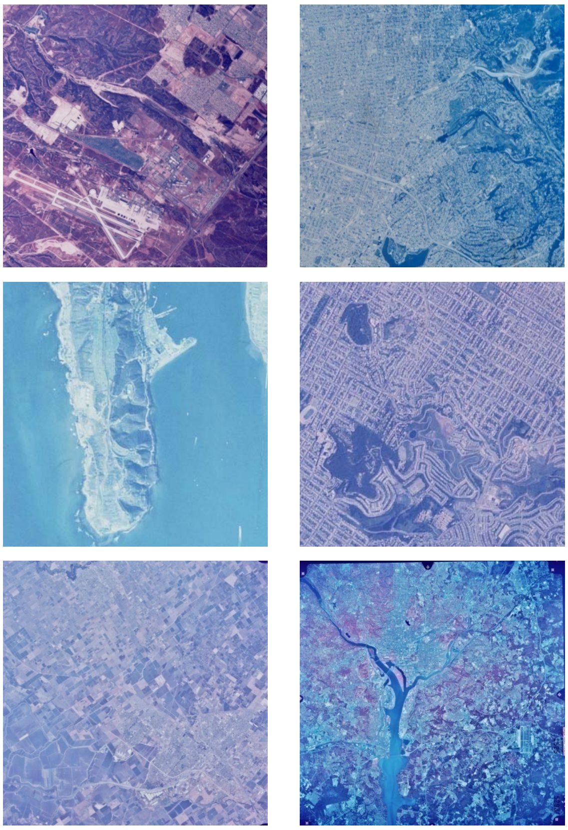
3) Using the OMP algorithm to solve $\boldsymbol{\alpha}$ according to the formula $\min\sum_{i=1}^{T}\lambda\|\boldsymbol{\alpha}_i\|_1+\frac{1}{2}\|\mathbf{I}_{HR}^i-\mathbf{H}\mathbf{D}_h\boldsymbol{\alpha}\|_2^2$ to calculate super-resolution remote sensing image block $\mathbf{I}_{HR}^i=\mathbf{D}_h\boldsymbol{\alpha}_i$.

4) Combine image blocks to output super-resolution remote sensing images.

III. EXPERIMENTAL VERIFICATION

In this part, the reliability of this algorithm is tested by experiment., the high resolution remote sensing image used in this experiment is obtained from the USC_SIPI high resolution remote sensing image library (http://sipi.usc.edu/database/database.php?volume=aerials&image = 6 # top), the remote sensing images in this library were screened, and six remote sensing images similar to the landscape of the Maoergai area in the upper reaches of the

Minjiang River were selected, as shown in the following Figure 1 :



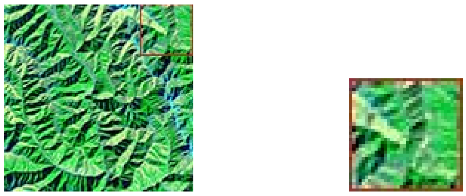
In the experiment, the magnification is c, the size of the high resolution remote sensing image block is $2m \times 2m$, and the inter-block coincidence pixel is m, the coincident pixels are randomly selected as 20,000 training blocks, and 16 atoms are used in the KSVD algorithm. Compared with the bicubic and nearest neighbor (NN) [15, 16, 17], the results of the overrun reconstruction are shown in Figure 2.

Figure 1. High resolution remote sensing image training exampler library

In the experiment, the reconstructed images are analyzed by the peak signal-to-noise ratio PSNR and the mean square error MSE. The results are shown in Table 1.

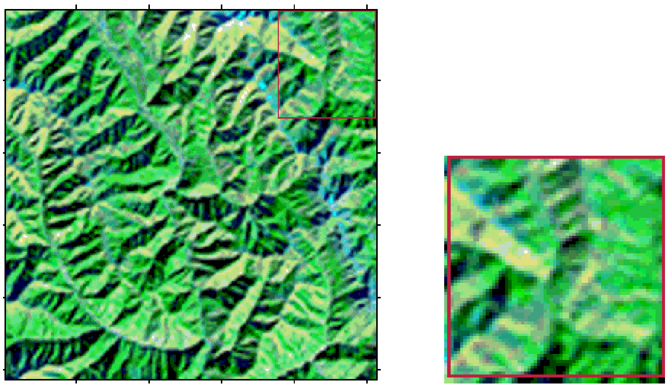
TABLE 1.THE COMPARISON OF THE PERFORMANCE PSNR (DB) AND MSE OF DIFFERENT ALGORITHMS

methods	PSNR(dB)	MSE
NN	22.482657	19.1605
This paper	23.4756	17.0907



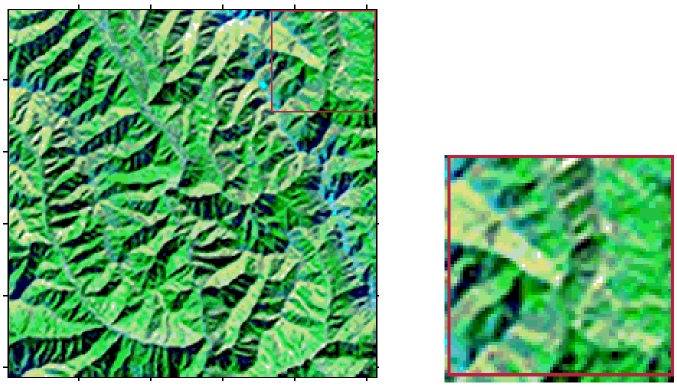
a. The input remote sensing image of 128*128

b. Image block in the upper right corner of figure a



c. the super-resolution reconstruction results(256*256) by the bicubic and nearest neighbor (NN)

d. Image block in the upper right corner of figure c



e. the super-resolution reconstruction results of this paper

f. Image block in the upper right corner of figure e

Figure 2. Super-resolution results of two different methods for a real remote sensing image

IV. CONCLUSION AND DISCUSSION

In this paper, K-SVD algorithm is used to study the exampler of high resolution image library, and the dictionary of high resolution remote sensing image is obtained. The low resolution image is represented by high resolution dictionary, and the remote sensing reconstruction of remote sensing image is realized. Which improves the peak noise ratio and mean square error of the image, and has better performance than the interpolation algorithm, which is more favorable for the subsequent processing. The algorithm is relatively simple, but has good effect. The algorithm obtains a pair of low resolution and high resolution dictionaries by training, and uses the case-based training block image to realize the remote sensing reconstruction of remote sensing image. The proposed algorithm can also be further improved, such as the use of backward projection, when the output of high-resolution images do not meet A, you can use the backward projection to make the image to meet this constraint, or can further explore the relationship between overlapping blocks, To further improve the speed of processing, etc., is the focus of the next step.

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