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The Separation of Remote Sensing Images Obtained by “The first satellite of high resolution” Based on Sparse Representation

Hong Wang

Sichuan Electromechanical institute of vocation and technology, Panzhihua, Sichuan, China

whiam@163.com

Abstract: Separating the high resolution remote sensing images is a difficult problem in the relative research field of remote sensing. In this paper a novel model separating the high resolution remote sensing images is proposed based on sparse representation, different dictionary which has an efficient description of different content of remote sensing image is obtained based on dictionary learning algorithm according to the characteristics of the high spatial resolution remote sensing images, separating by SSF algorithm. The experimental results of the remote sensing images obtained by “The first satellite of high resolution” show that the algorithm can separate features of remote sensing images better, and it is more robust.

Keywords: sparse representation, image separation, dictionary learning, SSF, the first satellite of high resolution

1. Introduction

With the development of electronic spectrum theory as well as electronic and computer technology, researchers have developed hyperspectral remote sensing (HRS) at full speed in recent years. Analyzing hyperspectral remote sensing data can yield abundant spectral information and detailed features [1]. At present, the method of Spectral Energy Level Matching (SELM) is widely used in the separation of remote sensing images, which is characterized by the spectral of features [2]. This method realized the separation according to the band intensity parameters and the waveform characteristics of the spectrum, but this method is easy to receive the interference of noise. In 2011, the object-oriented remote sensing image segmentation approach based on edge detection is proposed by Lian [3] etc., but the precision of this method is not high.

In this paper, a novel remote sensing image separation algorithm based on sparse representation is proposed which aimed at the high resolution, wide field imager, and the application of multiple load image mosaicing fusion of the "The first satellite of high resolution". The remote sensing image information can be divided into three categories, which are cartoon information, texture information and noise, separating by SSF algorithm. The experimental results of the remote sensing images obtained by "The first satellite of high resolution" show that the algorithm can separate features of remote sensing images better, and it is more robust.

2. The separation of remote sensing image based on sparse representation and dictionary learning

2.1 The basic model

For a set of pixels of hyperspectral image, let $\mathbf{x} \in \Re^M$, the fundamental goal of the dictionary learning method is to find a set of atomic signals $\mathbf{D} = [\mathbf{d}_{1,\dots}\mathbf{d}_K]$ to represent the hyperspectral data by a small number of terms in a linear generative model [4], i.e.

$$\mathbf{x} = \mathbf{D}\mathbf{y} + \boldsymbol{\varepsilon} \tag{1}$$

In this article, we use lowercase letters to represent vectors (such as x) and capital letters to represent matrixes. Moreover, $\boldsymbol{\varepsilon}$ is a small residual due to modeling $\mathbf{x}$ in a linear manner with the sparse representation vector $\mathbf{y} \in \Re^K$. The formulation of (1) is often a regularized least squares optimization as follows [5]:

$$\min \|\mathbf{x}\|_0 \quad \text{subject to} \quad \|\mathbf{y} - \mathbf{D}\mathbf{x}\|_2 \le \boldsymbol{\varepsilon} \tag{2}$$

In the field of image process, suppose that the observed signal is a superposition of two different sub-signals $\mathbf{y}_1$, $\mathbf{y}_2$, that is $\mathbf{y} = \mathbf{y}_1 + \mathbf{y}_2$, where $\mathbf{y}_1$ is sparsely generated by a linear generative model, and $\mathbf{y}_2$ is generated by another sparse model. The problem of remote sensing images separation is to separate the two sources. In the signal model, we should solve the following problem [6]:

$$\min \|\mathbf{x}_1\|_0 + \|\mathbf{x}_2\|_0 \ \text{subject to} \qquad \|\mathbf{y} - \mathbf{D}_1\mathbf{x}_1 - \mathbf{D}_2\mathbf{x}_2\|_2^2 \le \boldsymbol{\varepsilon}_1^2 + \boldsymbol{\varepsilon}_2^2 \tag{3}$$

The solution ($\hat{\mathbf{x}}_1$, $\hat{\mathbf{x}}_2$) would generate a plausible solution $\hat{\mathbf{y}}_1 = \mathbf{D}\hat{\mathbf{x}}_1$, $\hat{\mathbf{y}}_2 = \mathbf{D}\hat{\mathbf{x}}_2$ to the separation problem [7].

2.2 Image separation via SSF

In the recent years, there is a growing agreement that remote sensing images are a mixture of texture and cartoon part combined linearly, $\mathbf{y}_1$ and $\mathbf{y}_2$. When the measure or image have an additive zero-mean white Gaussian noise [8], $\mathbf{v}$, which have a known standard deviation δ.Suppose the measured image $\mathbf{y}$,the ideal image $\mathbf{y}_0$,then we can get:

$$\mathbf{y} = \mathbf{y}_0 + \mathbf{v} = \mathbf{y}_1 + \mathbf{y}_2 + \mathbf{v} \tag{4}$$

How can we recover the parts of $\mathbf{y}_0$, $\mathbf{y}_1$ and $\mathbf{y}_2$ the important goal of the remote sensing image processing. Using SSF formulation, we propose to solve:

$$\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2 = \arg\min \lambda \|\mathbf{x}_1\|_1 + \lambda \|\mathbf{x}_2\|_2 + \frac{1}{2}\|\mathbf{y} - \mathbf{D}_1\mathbf{x}_1 - \mathbf{D}_2\mathbf{x}_2\|_2^2 \tag{5}$$

The matrix $\mathbf{D}_1$ and $\mathbf{D}_2$ are to be chosen such that they enable sparse representation of texture and cartoon content respectively. The matrix $\mathbf{D}_1$ could contain oscillatory atoms, such as found in the Gabor transform or DCT transform. The matrix $\mathbf{D}_2$ could be wavelet, curvelet, contourlets or ridgelets which depend on the type of cartoon content we expect to find in the remote sensing images.

In this paper, the algorithm Separable Surrogate Functionals (SSF) method is used to solve the problem, which leads to the iterative update [9]:

$$\hat{\mathbf{x}}^{k+1} = S_\lambda(\frac{1}{c}\mathbf{D}^T(\mathbf{y} - \mathbf{D}\hat{\mathbf{x}}^k) + \hat{\mathbf{x}}^k) \tag{6}$$

Which is posed in terms of the combined dictionary and the combined representation as in (7). Breaking this into two representation parts as:

$$\begin{aligned} \hat{\mathbf{x}}_1^{k+1} &= S_\lambda(\frac{1}{c}\mathbf{D}_1^T(\mathbf{y} - \mathbf{D}_1\hat{\mathbf{x}}_1^k - \mathbf{D}_2\hat{\mathbf{x}}_2^k) + \hat{\mathbf{x}}_1^k) \\ \hat{\mathbf{x}}_2^{k+1} &= S_\lambda(\frac{1}{c}\mathbf{D}_2^T(\mathbf{y} - \mathbf{D}_1\hat{\mathbf{x}}_1^k - \mathbf{D}_2\hat{\mathbf{x}}_2^k) + \hat{\mathbf{x}}_2^k) \end{aligned} \tag{7}$$

Where the function $S_\lambda(\mathbf{r})$ is an element-wise soft-thresholding operation on $\mathbf{r}$ with a threshold λ, the parameter c should be chosen such that $c > \lambda(\mathbf{D}_a^T\mathbf{D}_a)$. Basically, the two dictionaries are redundant and full-rank[10]. So, denoting:

$$\begin{aligned}\mathbf{x}_1 &= \mathbf{T}_1\mathbf{y}_1 \rightarrow \mathbf{y}_1 = \mathbf{T}_1^{+}\mathbf{x}_1 = \mathbf{D}_1\mathbf{x}_1 \\ \mathbf{x}_2 &= \mathbf{T}_2\mathbf{y}_2 \rightarrow \mathbf{y}_2 = \mathbf{T}_2^{+}\mathbf{x}_2 = \mathbf{D}_2\mathbf{x}_2\end{aligned} \tag{8}$$

Which leads to an optimization problem as (9).

$$\hat{x}_1, \hat{x}_2 = \arg\min_{x_1, x_2} \lambda \|\mathbf{x}_1\|_1 + \lambda \|\mathbf{x}_2\|_2 + \frac{1}{2}\|\mathbf{y} - \mathbf{D}_1\mathbf{x}_1 - \mathbf{D}_2\mathbf{x}_2\|_2^2 \text{ subject to } T_1D_1x_1 = x_1 \text{ and } T_2D_2x_2 = x_2 \tag{9}$$

In formulation (9), $\mathbf{T}_1 = \mathbf{D}_1^{-1}, T_2 = D_2^{-1}$ .Where $\mathbf{x}_1$ and $\mathbf{x}_2$ is a column-span of $\mathbf{T}_1$ and $\mathbf{T}_2$.

2.3 Solve the separation problem

As formulation (7), formulation (9) can be solved by the very same iteration formula. The iteration induces a descent \n penalty, as formulation (10):

$$\begin{aligned}\hat{\mathbf{x}}_1^{k+\frac{1}{2}} &= S_\lambda\left(\frac{1}{c}\mathbf{D}_1^{T}(\mathbf{y} - \mathbf{D}_1\hat{\mathbf{x}}_1^{k} - \mathbf{D}_2\hat{\mathbf{x}}_2^{k}) + \hat{\mathbf{x}}_1^{k}\right) \\ \hat{\mathbf{x}}_2^{k+\frac{1}{2}} &= S_\lambda\left(\frac{1}{c}\mathbf{D}_2^{T}(\mathbf{y} - \mathbf{D}_1\hat{\mathbf{x}}_1^{k} - \mathbf{D}_2\hat{\mathbf{x}}_2^{k}) + \hat{\mathbf{x}}_2^{k}\right)\end{aligned} \tag{10}$$

Then, as formulation (8), formulation (11) can be get, actually it is a projection operation.

$$\begin{aligned}\hat{\mathbf{x}}_1^{k+1} &= \mathbf{T}_1\mathbf{D}_1\mathbf{x}_1^{k+\frac{1}{2}} \\ \hat{\mathbf{x}}_2^{k+1} &= \mathbf{T}_2\mathbf{D}_2\mathbf{x}_2^{k+\frac{1}{2}}\end{aligned} \tag{11}$$

At last, the output cartoon and texture remote sensing image can be get.

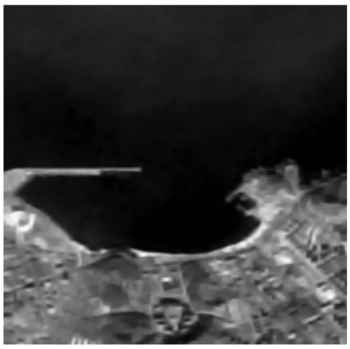
$$\begin{aligned}\hat{\mathbf{y}}_1^{k+1} &= \mathbf{D}_1 \bullet S_\lambda\left(\frac{1}{c}\mathbf{D}_1^{T}(\mathbf{y} - \hat{\mathbf{y}}_1^{k} - \hat{\mathbf{y}}_2^{k}) + \mathbf{T}_1\hat{\mathbf{y}}_1^{k}\right) \\ \hat{\mathbf{y}}_2^{k+1} &= \mathbf{D}_2 \bullet S_\lambda\left(\frac{1}{c}\mathbf{D}_2^{T}(\mathbf{y} - \hat{\mathbf{y}}_1^{k} - \hat{\mathbf{y}}_2^{k}) + \mathbf{T}_2\hat{\mathbf{y}}_2^{k}\right)\end{aligned} \tag{12}$$

3. Simulation experiment

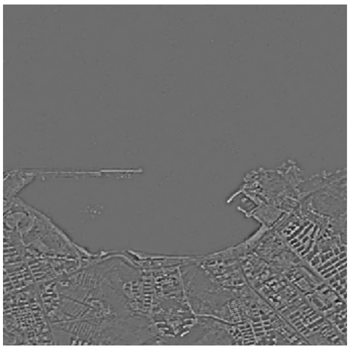
In this section, the performance of the algorithm is tested. The remote sensing image of “The first satellite of high resolution” is obtained from the national space administration of China. Which is the image of Haian county of Shandong province, and the image size is 512*512.

The dictionary chosen for this separation are DCT transform for the texture part and curvelet for cartoon, and the standard deviation δ of additive white Gaussian noise is 15. Figure 1 shows the results of this experiment. We can see that the cartoon, texture and noise parts of the remote sensing image are separated very well.

(a) The origin remote sensing image



(b) The cartoon part of the image



(c) The texture part of the image

Figure 1. The origin remote sensing image (left), the cartoon part(middle), the texture part(right)

We can see that the remote sensing image can be separated better by spare representation. Also, we can detect the city and the building from texture part of the remote sensing image. This is very important in practical application.

4. Conclusion

In this paper, a novel model of separating the high resolution remote sensing images is presented, different dictionary is obtained according to the characteristics of the high spatial resolution remote sensing images. The experiments on “The first satellite of high resolution” image showed that the remote sensing images separation based on sparse representation has a better effect. This method can be used in edge detection and remote sensing image denoising. The next step of the study is the optimization of the algorithm and the expansion of application.

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