A structured sub-pixel target detection method base on manifold learning method

Bo Du*[a], Dengyi Zhang[a], Pingxiang Li[b], Tao Chen[c], Ke Wu[c]
[a]School of Computer, Wuhan University, Wuhan, China ;
[b]LIESMARS, Wuhan University, Wuhan, China;
[c] Institute of Geophysics and Geomatics,
China University of Geosciences, Wuhan, Chinaa

ABSTRACT

The manifold learning theory is firstly used to transform the hyperspectral images into a low-dimension feature spaces. The reconstruction error is computed to get discriminative information. Then a structured matched subspace detector is developed. This method can effectively avoid the contamination by targets and spectral anomalies to backgrounds subspace and detect sub-pixel targets with better performance than traditional methods.

Keywords: Manifold Learning, target detection, hyperspectral images

1. INTRODUCTION

Many airborne platforms, such as Unmanned Aerial Vehicles (UAV), can be equipped with various sensors, such as photoelectric sensors, infrared sensors, and SAR sensors. Among the remote sensed images by these airborne platforms, hyperspectral images (HSI) draw much research interest since they can reveal minor spectral difference between those visually very similar objects. However, due to the limitation of spatial resolution, targets of interest in HSIs occupy only part of a pixel. These targets and different ground objects together compose the mixed pixels [1]. How to detect these sub-pixel targets in the mixed pixels is of great interest in the hyperspectral target detection domain [2-6].

Methods based on linear mixture model are widely used. These methods have physical meaning and can provide quantitive detection results with good detection probability. These methods can be divided into two kinds: spectrum unmixing methods and generalized likelihood rate test methods. Fully constrained linear separation (FCLS) methods [7] are typical spectrum unmixing ones which can extract the abundances of different endmembers including the targets endmember. However, because of the spectral variance of targets, this kind of methods can not provide the reliable rule to separate targets and background and the qualitative detection result is poor. Generalized likelihood ratio test methods, such as Adaptive Matched Subspace Detector (AMSD)[2], provides a statistical model to separate the target pixels and background pixels, but can't give quantitative detection results. Besides, all the above methods would show reduced performance when the endmembers number is underestimated or overestimated [8].

This paper proposes a manifold learning based structured detection (MLSD) method, combining the manifold learning and adaptive matched subspace, which can not only construct a robust subspace structure but also separate the targets and the background with statistically reliable rule.

2. METHODOLOGY

2.1 Manifold Analysis

For the remote sensing image, the space distribution of pixels is characterized by correlation, that is to say, the type information of a given pixel is most likely to be the same as that of its neighborhood pixels. However, the present calculation method does not take this space correlation of pixels in the image into consideration. Each pixel in the hyper dimensional characteristic space is regarded as a different isolated point. The feature of the remote sensing image cannot be made full use of. In view of the above problems, this paper puts forward a selection method which suits the correlatbbive LLE(Locally Linear Embedding) feature of the neighbors. To be more specific, when searching for the

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neighboring point, the object is no more a single pixel, but all the neighboring pixels in the space. If two pixels are approximate to each other, but their neighboring pixels present significant differences, we will still give the relatively bigger value to the distance between the two pixels, i.e., we will not restructure the said data points by using them as neighboring points any more. Therefore, the noise will not be considered, thus increasing the robustness of the target detection method [9].

This algorithm can come down into 3 steps: ① identify "k" neighboring points of each sample point; ② work out the local restructure weight matrix of the said sample point according to its neighboring points; ③ work out the output value of the said sample point based on the local restructure weight matrix and its neighboring points. Detailed descriptions are referred to in [9].

After the transformation above, the image dataset are projected into a low-dimension feature space. Beside, the reconstruction weights of the neighbor points of each vectored point are computed. The k-nearest neighbor points are used to compute the construction weight and the construction error is defined as:

$$\varepsilon_i = \left\| x_i - \sum_{x_j \in \mathrm{N}_i} \omega_{ij} x_j \right\|^2 \tag{1}$$

where $\sum_{x_j \in \mathrm{N}_i} \omega_{ij} = 1$ and $\omega_{ij} = 0$ when $x_j \notin \mathrm{N}_i$ (N_i refers to x_i 's neighboring pixels) are the two constrains.

After the manifold analysis, the embedded low dimension datasets and the discriminative information can be obtained. In other words, the datasets are divided into two parts: one is the probable targets areas with large reconstruction errors and the other with small errors being background areas.

2.2 structured matched subspace detector

In the linear mixed model, the reflectance ratio of a pixel at a certain spectral band can be presented as the inear combination of its end member characteristic reflectance ratio and the corresponding abundance[7]. Therefore, the reflection ratio of the pixel at the "i" wave band can be expressed as:

$$r_i = \sum_{j=1}^{m} h_{ij} \partial_j + \varepsilon_i \tag{2}$$

where, ri refers to the reflection ratio of the "i" waveband of mixed pixels; hij refers to the reflection ratio of the "j" end member of the "i" waveband; ∂_j refers to the abundance of the "j" end member of the said pixel; ε_i refers to the random image noise of the "i" waveband; $i = 1, 2, \cdots, n$; n refers to the number of wave amplitudes; $j = 1, 2, \cdots, m$; m refers to the number of selected end members.

If all wavebands are considered for, the matrix of equation (1) shall be:

$$\boldsymbol{R} = \boldsymbol{H}\partial + \varepsilon = d\alpha_p + U\gamma + \varepsilon \tag{3}$$

where, R is a n-dimensional column vector, representing reflection ratio at each waveband of mixed pixels; H is a matrix of n row and m column, and its each column shows the spectral vector of m end members; ε is a n-dimensional random noise, which is usually not considered in linear mixture model.

During the detection process, only the spectrum of the targets to be detected is known, so it is necessary to further classify the matrix H in the equation (3) into target spectrum to be detected and the other end member spectrum. This classification can be expressed as $(u_1, \cdots, u_{m-1}, d)$ and in addition, it is assumed that $U = (u_1, \cdots, u_{m-1})$. The column vector d refers to the spectrum of the targets to be detected, and ui refers to the other end member signal in the image.

Accordingly, convert ∂ into α_p and γ , and assume γ refers to the abundance of end members, while α_p refers to the abundance of target spectrum d.

Then, the maximum likelihood method is used to estimate the parameters, such as the estimation of background endmembers' abundances and the estimation of noise variance. The estimation of background endmembers' abundances is:

$$\hat{a}_b = (B^T B)^{-1} B^T x \qquad (4)$$

where $\hat{a}_b$ is the abundance of background endmembers, B is the background endmembers matrix, x is the vector composed of the reflectance of different components of a pixel.

And the estimation of the variance of noise is:

$$\hat{\sigma}^2 = \frac{1}{L}(x - B\hat{a}_b)^T (x - B\hat{a}_b) \qquad (5)$$

Then, a detector based on generalized likelihood rate test theory is figured out as:

$$f_1 = \left[\frac{2\pi}{L} x^T (I - E(E^T E)^{-1} E^T) x\right]^{\frac{L}{2}} \exp(-\frac{L}{2}) \qquad (6)$$

$$f_0 = \left[\frac{2\pi}{L} x^T (I - B(B^T B)^{-1} B^T) x\right]^{\frac{L}{2}} \exp(-\frac{L}{2}) \qquad (7)$$

where L is the dimension of the image, E is the full endmembers matrix including the targets endmember,

Finally, the AMSD detector is:

$$D_{AMSD} = \frac{f_1 - f_0}{f_0} = \frac{x^T (E(E^T E)^{-1} E^T - B(B^T B)^{-1} B^T) x}{x^T (I - E(E^T E)^{-1} E^T) x} = \frac{x^T (P_B - P_Z) x}{x^T P_Z x} \qquad (8)$$

3. EXPERIMENTS AND ANALYSIS

In this experiment, the simulated data is obtained by embedding targets into the PHI (Pushbroom Hyperspectral Image) data. The data was imaged in the Xiaoqiao area in Jiangsu province and the spectral range is 417.4*nm*-854.4*nm* with a spectral resolution of 5*nm* and a size of 240×240. The target spectrum is the andradite selected from the standard spectral library in the software ENVI, which is shown in Fig. 1(a). And the target spectrum is added into 100 pixels in the image to get 100 target pixels. The target pixels are divided into 10 groups by the adding abundances, and the abundances of each group from the top to the bottom in the image are: 100%、90%、80%、 , ······ , 30% , 20% , 10%. The noise with a SNR of 30:1 is also added. The synthetic method is presented as:

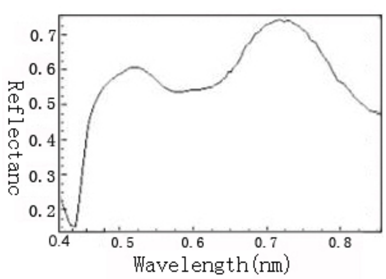
$$\boldsymbol{s} = p\boldsymbol{t} + (1 - p)\boldsymbol{b} \qquad (9)$$

where $\boldsymbol{t}$ is the spectrum of the target, $\boldsymbol{b}$ is the original spectrum of the pixel, $\boldsymbol{s}$ s the spectrum of the pixel after adding the target spectrum, p is the adding abundance of the target spectrum.

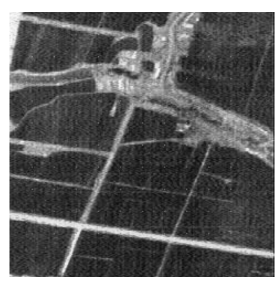
In our experiments, the fully constrained linear separation (FCLS) based method and the conventional adaptive subspace matched detector (AMSD) are also used to compare the different performances of them and our proposed method. The true information about the image scene is known beforhand, so we can determine the right number of endmembers before detection (in the experiment it is 6) and select the exact endmembers from the image for both FCLS and AMSD. However, in most cases, it is difficult to get the true information about the image scene. Accordingly, underestimation and overestimation of the number of endmembers is usual. In order to verify the effect of our method, we investigate the performance of the above methods with the varying of the number of endmembers. Our proposed MLSD uses the same number as the dimension of projected feature space.

First, we take the endmembers number as 6 and apply the proposed method, FCLS based method and AMSD based method. Fig. 1(c) is the result image of our proposed method. We investigate the different probability of false alarm (PFA) under the same probability of detection (PD). Under a PD of 100%, we divide the images by a suitable threshold and obtain the final results shown in Fig.1 (d), (e) and (f). From Fig.1, under the same PD, our proposed method has a PFA of only 2%, while FCLS has 12% and AMSD has 6%. It is concluded that comparative to FCLS and AMSD based method our proposed method has higher PD under the same PFA.

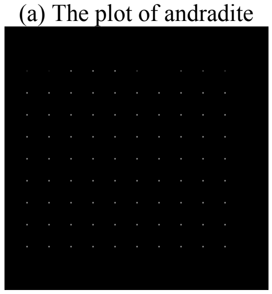
Then we take the number of endmembers as 5 and 7 according to the under estimation and overestimation of the number of endmembers and apply the three methods to detect the sub-pixel targets. Again, we compare their different PFA under a PD of 100%. The results are listed in Tab.1, which shows that for each method, the PFA under the right number of endmembers is lowest. Meanwhile our MLSD presents the lowest PFA than the other two in each case and keeps low PFA steadily across all the cases. It is concluded that our proposed method can present better performance at variable cases.



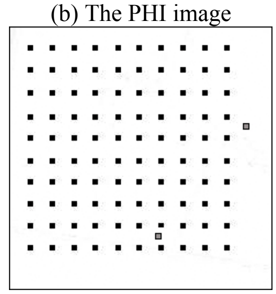
(a) The plot of andradite



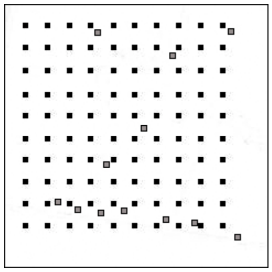
(b) The PHI image



(c) Result of our method



(d) Division results of our method


(e) Division results of FCLS

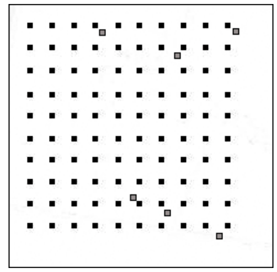

(f) Division results of AMSD

Fig. 1 The simulated image and the detection results in the experiment

Table 1 Detection results of the three methods

Number of endmembers	PFA		
	Our method	FCLS	AMSD
5	2%	17%	9%
6	2%	12%	6%
7	4%	21%	11%

CONCLUSIONS

This thesis proposes a manifold learning based structured detection (MLSD) method. Locally linear embedding is used to exclude the probable targets from background information, then the structured background subspace detection method can be constructed from the left background datasets. Experiments reveals it performs better in detecting sub-pixel targets than traditional structured methods and it is less sensitive to the variable dimensions of lowed dimension feature space.

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