The Endmember Analysis for Sub-Pixel Detection Using the Hyperspectral Image

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Abstract: In the middle-resolution remote sensing, the Ground Sampled Distance(GSD) sensed and sampled by the detector is generally larger than the size of objects(or materials) of interest, in which case several objects are embedded in a single pixel and cannot be detected spatially. This study is intended to solve this problem of a hyperspectral data with high spectral resolution. We examined the detection algorithm, Linear Spectral Mixing Model, and also made a test on the Hyperion data. To find class Endmembers[1], we applied two methods, Spectral Library and Geometric Model, and compared them with each other.
Keyword: Hyperspectral Image, Endmember, Linear Spectral Mixing Model

1. Introduction

Detection in remotely sensed images can be conducted spatially, spectrally or both [2]. If the images have high spatial resolution, materials can be detected by using spatial and spectral information, unless we can't see the object embedded in a pixel. In this paper, we intend to solve the limit of spatial resolution by using the hyperspectral image which has high spectral resolution. Therefore, the Linear Spectral Mixing (LSM) Model which is sub-pixel detection algorithm is used to solve this problem. To find class Endmembers, we applied two methods, Spectral Library and Geometric Model, and compared them with each other.

From the result of sub-pixel detection algorithm, we can see the detection of water is satisfied and the object shape cannot be extracted but the possibility of material existence can be identified.

2. Linear Spectral Mixing Model

In image classification which is widely used method for extracting surface information, each pixel is assigned to one of several known categories or classes through a statistical separation approach. But a pixel observed by the remote sensing instrument consists of mixed materials. Therefore, the LSM Model for determining the relative abundances of materials that are depicted in multispectral or hyperspectral image based on the materials' spectral characteristics is used to solve this spectral mixing problem.

1) Abundance

In the LSM Model, the spectrum of a mixed pixel is represented as a linear combination of component spectra (Endmember). The weight of each Endmember spectrum is proportional to the fraction of the pixel area (Abundance) covered by the Endmember [4]. Therefore, the general equation for mixing by area is given by

$$x = \sum_{k=1}^{M} a_k s_k + w \tag{1}$$

Where,

- x : spectrum of the mixed pixel
- s_k : spectra of the endmembers
- a_k : their abundances
- M : number of the endmembers
- w : N - dimensional error vector for lack-of-fit

Physical considerations dictate the following constrains which can be enforced to guarantee meaningful parameter values.

$$1 \ge a_k \ge 0, \quad \sum_{k=1}^{M} a_k = 1 \tag{2}$$

If expending the equation (1), the pixel value matrix (column) of N - dimension is as follows.

$$_N X_1 = {}_N S_M \, {}_M A_1 + {}_N W_1 \tag{3}$$

Where, $M < N$

Using the Least Square concept, we can get the value of abundance from equation (4).

$$A = (S^T S)^{-1} S^T X \tag{4}$$

[1] the spectral signature for a pure surface

2) RMSE

Residuals over all bands for each pixel in the image can be averaged to give a Root-Mean Square (RMS) error, portrayed as an image, which is calculated from the difference of the modeled ($x(n)$) and measured ($\hat{x}(n)$) pixel spectrum as

$$RMSE = \left(\sum_{n=1}^{N} \left\| x(n) - \hat{x}(n) \right\|^{2}\right)^{\frac{1}{2}} \qquad (5)$$

3. Implementation

1) Data

The Hyperion data sampled with the sensor of EO-1 satellite is used to demonstrate this LSM Model. Spatial resolution has 30m which is equal to Landsat ETM+ and swath width is approximately 7.7km. In this data, 242 bands which are whole data is extracted to 125 bands that noise on image is removed and the subset image of 30×30 pixels at Anyang in Korea is chosen for study area (Fig. 1).

Fig. 1. Study Area

2) Endmember Determination

Given the resulting spectrum and the Endmember spectra, the linear spectral mixing is solving for the abundance values of each Endmember for every pixel. The Endmember determination is significant for LSM model because LSM Model results are highly dependent on the input Endmembers and changing the input Endmembers has an influence on the results.

In this paper, two methods, Spectral Library and Geometric Model, are applied and compared with each other. As one of the Endmember determination methods, we can use the Spectral Library which is libraries of spectral reflectance. USGS (U.S. Geological Survey), JPL (NASA Jet Propulsion Lab.), and JHU (Johns Hopkins Univ.) offer this library information. Other technique developed to extract Endmember spectra is Geometric Model. Generally it involves the performance of the set of all scene pixels as a scatter plot in spectral space or some subspace thereof.

To compare each method, three Endmembers are selected from Spectral Library (extracted from JHU, Fig. 2) and subset image (Approximately 10 pixels each Endmember are trained from 2D scatter plot, Fig. 3).

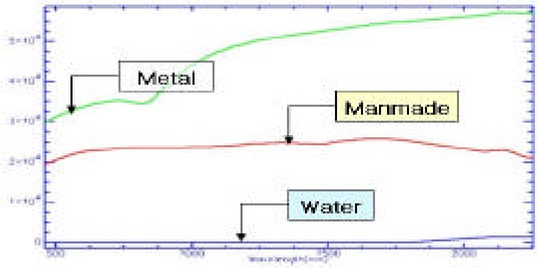

Fig. 2. Endmembers from Spectral Library

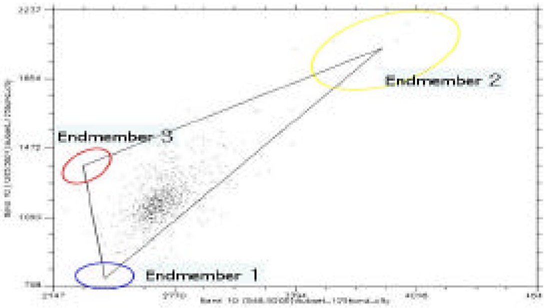

Fig. 3. Endmembers from 2D scatter plot

3) Result

The results of LSM Model appear as a series of gray-scale images, one for each Endmember, plus a RMS error image. Higher abundances (and higher errors for the RMS error image) are represented by brighter pixels (larger floating-point numbers) [7]. From the RMS error image, we can determine areas of missing or incorrect Endmember. When the RMS error image doesn't have any more high errors, then the LSM Model is completed.

For the visual estimation, the images are processed to 2% linear stretch and the brightest pixel is calculated of abundance value for quantitative approach.

① Case 1

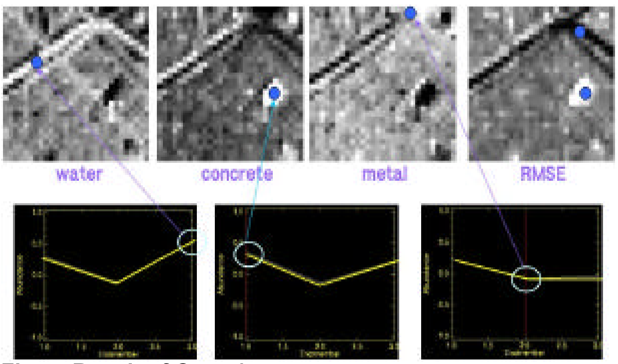

Fig. 4. Result of Case 1

Table 1. Result of Case 1

	water	concrete	metal		RMSE
Abun.	0.54	0.36	-0.07	Max.	430.4
RMSE	475.7	762.6	482.7	Min.	762.6

The case 1 is to study the detection of water on the city region. Water, Metal, and Concrete are trained for Endmembers of case 1. We can identify the small stream which can't be detected with image classification and RMS error value of water pixel (But it is higher than case 2) is lower than any other (water: 475.7). High RMS error shows that the LSM Model may be repeated. In this result we can find that the water detection image is discriminated with the concrete detection image.

② **Case 2**

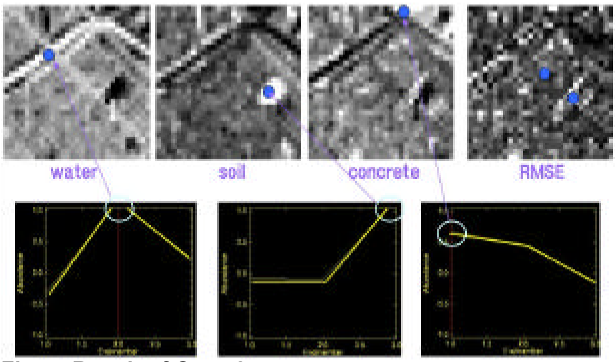

Fig. 5. Result of Case 2

Table 2. Result of Case 2

	water	soil	concrete		RMSE
Abun.	1.16	0.98	1.17	Max.	25.16
RMSE	35.65	40.30	26.59	Min.	84.46

In the case 2, Water, Concrete, and Soil are trained. We can also identify the small stream in the result of case 2 image and the water detection image is discriminated with the soil detection image. RMSE value is lower than RMSE of case 1 (25.16~84.46). Each abundance generally is higher than case 1 (water: 1.16, metal: 1.17).

4. Conclusions

In this paper, we examined the detection algorithm, LSM Model, and also made a test on the Hyperion data. To find a class Endmember, we applied two methods, Spectral Library and Geometric Model, and compared them with each other.

From the result of sub-pixel detection algorithm, we can see the detection of water is good and the object shape cannot be extracted but the possibility of material existence can be identified.

We can find some problems in this study. First, actually the sum of each abundance is not 100% ($\sum_{k=1}^{M} a_k = 1$) and negative value is appeared ($1 \geq a_k \geq 0$). And also we know the best way to correct the problems is to run the algorithm iteratively and to examine the abundance images and RMS error image. Second, Endmember is important to solve the detection algorithm Therefore, the study on the Endmember determination must be presented for better result of Mixing Model. Third, LSM Model is limited to apply the Least Square concept, because the noise of atmosphere effect or signal processing is systematic error.

Study on the Endmember determination will be required for the good result. Image preprocessing techniques - radiometric correction and dimension reduction – must be applied to remove the systematic error.

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