REFINED TARGET RECOGNITION IN HYPERSPECTRAL IMAGERY BASED ON SPECTRAL REFLECTANCE AND DERIVATIVE INFORMATION

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1. INTRODUCTION

A hyperspectral image can be considered as an image cube where the third dimension is the spectral domain represented by hundreds of spectral wavelengths. A hyperspectral image pixel is actually a column vector with dimension equal to the number of spectral bands and contains valuable spectral information that can be used to detect and identify a variety of nature and man-made material. Some spectral similarity measures are advanced such as spectral angle mapper (SAM), spectral correlation mapper (SCM), spectral information divergence (SID) etc [1]. They make use of spectral reflectance only that is limited and is a challenge for refined target. In this paper, a new recognition algorithm is proposed, which includes two key techniques: one is the cooperation of spectral reflectance and derivative information, and the other is the fusion of the preliminary target recognitions from different channels. The algorithm proposed is effective in recognizing refined target in hyperspectral imagery.

2. BACKGROUND

Spectral similarity provides an importance feature in material identification, and discrimination and detection. Many pixel-based spectral similarity measures have been used for this purpose. The early and classical spectral discrimination measure is spectral angel mapper (SAM), which will be taken as an example in this paper [2]. Spectral derivative analysis involves taking the slope information from the reflectance curve over the available wavelengths in the spectrum [3]. The first and second derivatives are presented in this part.

2.1. Spectral angel mapper (SAM)

Assume that $\mathbf{X}=(x_1,x_2,...,x_n)$ and $\mathbf{Y}=(y_1,y_2,...,y_n)$ are two spectral signatures. The SAM measures spectral similarity by calculating the angle between the spectral signatures $\mathbf{X}$ and $\mathbf{Y}$

$$\mathrm{SAM}(\mathbf{X},\mathbf{Y})=\cos^{-1}\left(\frac{\mathbf{X}\cdot\mathbf{Y}}{|\mathbf{X}|\cdot|\mathbf{Y}|}\right) \tag{1}$$

where $\mathbf{X}\cdot\mathbf{Y}=\sum_{i=1}^{n}x_iy_i$, $|\mathbf{X}|=(\sum_{i=1}^{n}x_i^2)^{1/2}$, $|\mathbf{Y}|=(\sum_{i=1}^{n}y_i^2)^{1/2}$.

2.2. Spectral derivative

The spectrum extracted from the hyperspectral data is a function of the wavelength λ, which can be represented in discrete form as

$$s = [s(\lambda_1), s(\lambda_2), s(\lambda_3), ..., s(\lambda_n)] \quad (2)$$

where $s(\lambda_i)$ is the reflectance value at wavelength λ_i (the value at the i^{th} band). The first derivative can be approximated by

$$\left.\frac{ds}{d\lambda}\right|_i \approx \frac{s(\lambda_j) - s(\lambda_i)}{\Delta\lambda} \quad (3)$$

where $\left. ds/d\lambda \right|_i$ is the first derivative at wavelength λ_i, $\Delta\lambda$ is the interval between adjacent bands, $\Delta\lambda = \lambda_j - \lambda_i, \lambda_j > \lambda_i$.

The second derivative can be derived from the first derivative as

$$\left.\frac{ds^2}{d\lambda^2}\right|_j \approx \frac{s(\lambda_i) - 2s(\lambda_j) + s(\lambda_k)}{(\Delta\lambda)^2} \quad (4)$$

where $\left. ds^2/d\lambda^2 \right|_j$ is the second derivative value at wavelength λ_j, and $\Delta\lambda = \lambda_k - \lambda_j = \lambda_j - \lambda_i, \lambda_k > \lambda_j > \lambda_i$.

The interval $\Delta\lambda$ between bands is closed related to the magnitude and resolution of the spectrum and have an important impact both on the wavelength location of influence points and on that of zero cross-over. In this paper, $\Delta\lambda$ is assumed to be constant and selected to be close to the spectral resolution of the original data.

3. PROPOSED METHODOLOGY

The framework proposed in this paper is illustrated in Fig. 1. There are two spectral signatures; one is unknown material spectrum, and the other is the spectrum from the spectral library. Firstly, calculate the 1st and 2nd spectral derivative of the two spectral signatures; the spectral derivatives are concatenated with the reflectance values as shown in the Fig. 1. Secondly, we can treat the 1st and 2nd spectral derivatives as new pixel vectors, and then calculate their vector angles together with the original spectra. Thirdly, the results after SAM are constrained by different thresholds, and the preliminary target recognitions are given. Finally, a soft decision fusion technique is used to fuse the different results from three channels.

In the framework, the benefits of spectral derivative or slope information from reflectance information are explored. The derivative of a spectrum can precisely model changes in the shape of the original spectrum and is sensitive to the spectral variations, especially the excursion in abscissa axis, which will change with the environment changed. After derivation, the distance between two materials that may not be discriminated by

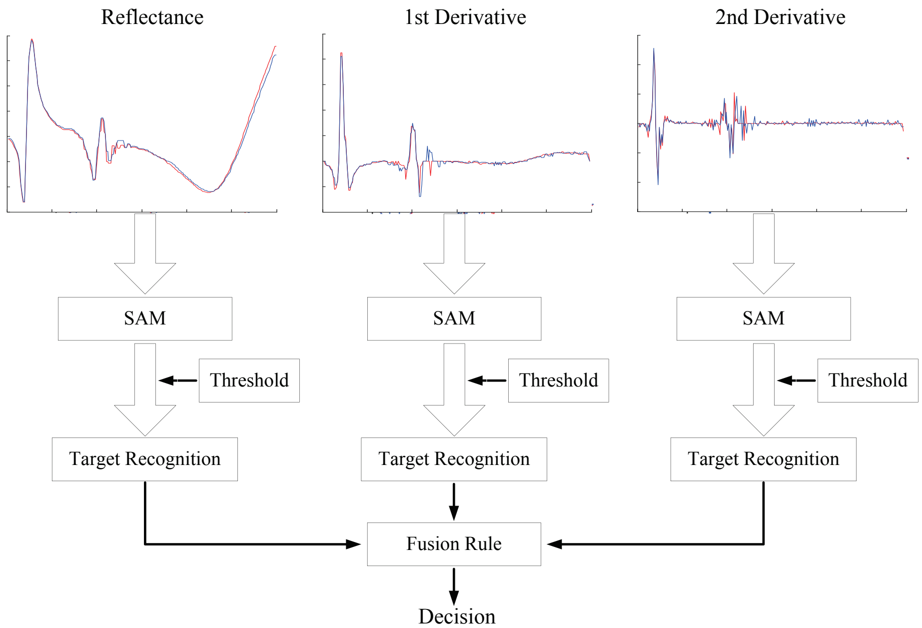

Fig.1. The proposed framework

SAM has widened, which is proved as shown in Table I in Part 4. However, the shortcoming brought by derivation is the amplification of noise, so a fusion rule is employed to make a decision next. We arrive at a final recognition by decision fusion based on majority voting [4].

4. EXPERIMENTAL RESULTS

A real hyperspectral image data from airborne visible infrared imaging spectrometer (AVIRIS) sensor were used for experiments. The AVIRIS image was acquired by 224 bands with a spectral coverage from 0.4 μ m to 2.5 μ m. However, we choose 197 bands by discarding water absorption and low SNR bands. In order to evaluate the proposed algorithm, two experiments are conducted.

To test the improvement of SAM through derivation, we got a spectral vector from the hyperspectral image. Then we calculated the vector angles of the original spectral, the 1st and 2nd spectral derivatives between the spectral vector and five spectra from spectral library respectively. As shown in the Table I, a correct recognition is marked by underline, while a line-through indicates a wrong recognition. The results of SAM by the original spectral are very near, and couldn't be used almost. In contrast, the 1st spectral derivative did well, and the 2nd spectral derivative did better.

Then we tested our algorithm to identify refined target comparing with SAM algorithm. The receiver operating characteristics (ROC) curves comparing the two algorithms are shown in Fig. 2. The experiment results indicated the proposed algorithm could have a better performance than the conventional SAM algorithm. When the false-alarm probability was 0.08%, the detection probability was increased by 5 percent.

Table I. The vector angles between the spectral vector and five spectra from spectral library

Materials / SAM	M1	M2	M3	M4	M5
Original	~~0.0302~~	~~0.0301~~	0.0855	0.1224	0.0941
1st derivative	0.1783	0.2310	0.3747	0.4412	0.3676
2nd derivative	0.3401	0.5137	0.8542	1.1732	0.9297

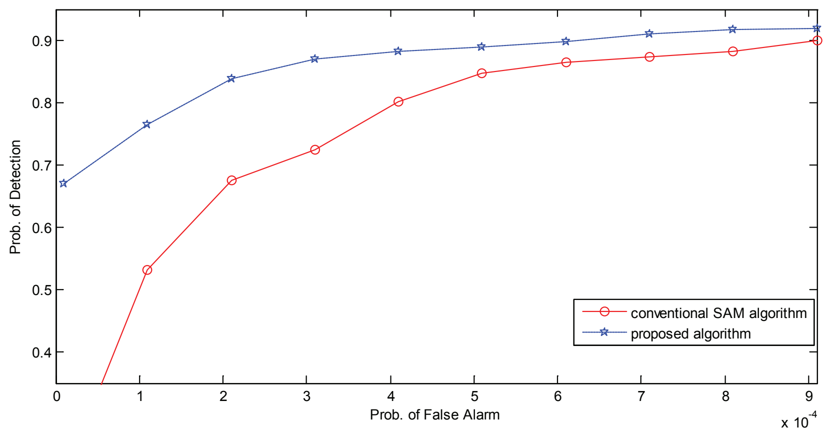

Fig.2. ROC curves comparing the proposed algorithm and conventional SAM algorithm

5. CONCLUSION

In this paper, a recognition algorithm based on spectral reflectance and derivative information is proposed for refined target recognition in hyperspectral imagery. It takes advantage of not only reflectance information but also derivative information fully. The conventional spectral similarity measures neglect the slope information of the spectral signature, and may be very likely to fail or sometimes may even identify wrong target when the materials' spectra are mostly similar. The cooperation recognition algorithm with derivatives can be sensitive to tiny difference and be effective in identifying refined target.

6. REFERENCES

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