A STUDY ON INFORMATION EXTRACTION FROM HYPER SPECTRAL IMAGE BASED ON SAMC & EPV

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ABSTRACT:

Spectral reflectance in hyper spectral image provides useful information of surface objects. In this paper, two algorithms have been introduced, and the characteristics of the two main types of algorithms are discussed: spectral angle mapping classification (SAMC) is used to identify objects and endmember projection vector (EPV) to distinguish between object and its background. And then, a new method integrated SAMC with EPV has been explored and proved by experiment to extract hyper spectral information. The result indicates that a combination of spectral angle mapping classification and endmember projection vector can evidently improve the precision of hyper spectral information extraction.

1 INTRODUCTION

Hyperspectral remote sensing is one of the great technological breakthroughs made in earth observing by human in recent years. As the frontier of current remote sensing, it is the technique of acquiring information in many very narrow, contiguous bands throughout the visible, near infrared, middle infrared and thermal infrared of the electromagnetic spectrum (Lillesand and Kiefer, 2000). The earth surface image obtained via hyperspectral imaging contains three attributes of spatial, radiate and spectral, which represents the spatial distribution of the objects and is likely to get radiant intensity and spectrum information of one of the pixels or group of pixels. Carrying abundant feature information of ground object, hyperspectral remote sensing data can be used to study the spectral information of the object from nanometer band level. This increased spectral resolution can assist in the identification of features that coarse multispectral sensors cannot differentiate (Brian Zutta, 2003).

A great of helpful research has been explored in hyperspectral information extraction. Traditional classification algorithms, such as SAM, have been widely used to extract hyperspectral information of objects. Landgrebe D. proposed a feature extraction algorithm to determine a feature subspace that is optimal for discriminating between the specific classes defined (Landgrebe D., 1999). Geng X.R., et al. developed an algorithm of surface objects extraction in hyperspectral image based on endmember projection vector (Geng X.R., et al., 2005). Kruse, F.A., et al. investigated how to extract compositional information for trafficability mapping from hyperspectral data (Kruse, F.A., et al., 2000). Wan Y. Q. et al. comparatively studied different classification accuracies of hyperspectral remote sensing images by using traditional classification algorithms provided with ENVI (Wan Y. Q., 2004).

How to extract ground objects from a hyperspectral image and gain the best separation between the objects and the background is one of the key questions in hyperspectral remote sensing application. Generally, the research in the world on information extraction from hyperspectral data is mainly based on the similarities between the spectrums. To a great extent, it is a mapping to the image.

This paper explores the AVIRIS image data by using endmember projection vector (EPV) algorithm (Geng X.R., et al., 2005) according to the geometric property of the hyperspectral image on the basis of spectral angle mapping classification (SAMC).

2 ALGORITHM DESCRIPTION

2.1 Spectral Angle Mapping Classification（SAMC）

Spectral angle mapping classification is a spectral classification based on physics, which matches pixels with reference spectrums using N dimension angles. It is based on the idea that an observed reflectance spectrum can be considered as a vector in a multidimensional space, where the number of dimensions equals the number of spectral bands. This is shown in figure 1, where a two-band "spectrum" will lie somewhere along a line passing through the origin of a two dimensional space. Under low illumination conditions (shadows), the length of the vector will be short. If the illumination is increased the length of the vector will increase. It is a self-acting classification to estimate the similarity between two spectrums by comparing image spectrum with individual or that in spectral library (Boardman, unpublished data; CSES, 1992; Kruse, et al., 1993a) and by calculating the angle between the two spectrums.

In hyperspectral image analysis, a spectral angle α, taking radian as unit, will be determined for each image spectrum (pixel) to evaluate the corresponding pixel of the output image in spectral angle mapping classification according to the selected reference spectral graph. If the spectral angle between the two materials is smaller than a given tolerance level, the spectrum is considered to be matched. At last, each reference spectral graph will produce an output image. Therefore, SAMC will generate a new data body, whose band number is equal to that of reference spectrum used in classification. As a rule, the gray threshold will be employed to match the area selected by experience with reference spectrum at best and hold the space coherence.
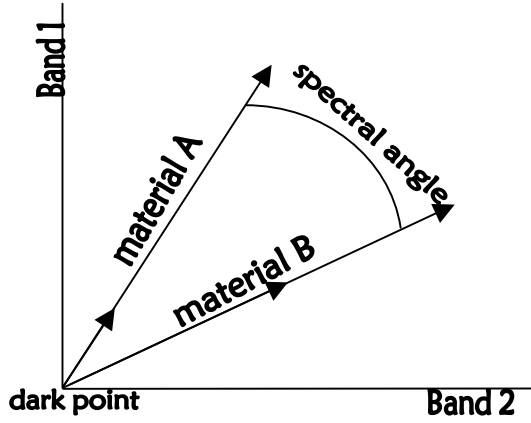
Fig.1 Two-dimensional Spectral Angle

In N (band number) dimensional vector space, the similarity between unknown spectrum t and reference spectrum r can be determined by the following formula:

$$\alpha = \cos^{-1}\left(\frac{\vec{t}\cdot\vec{r}}{\|\vec{t}\|\cdot\|\vec{r}\|}\right) \qquad (1)$$

The above formula can also be adapted:

$$\alpha = \cos^{-1}\left(\frac{\sum\limits_{i=1}^{N} t_i r_i}{\left(\sum\limits_{i=1}^{N} t_i^2\right)^{\frac{1}{2}}\left(\sum\limits_{i=1}^{N} r_i^2\right)^{\frac{1}{2}}}\right) \qquad (2)$$

Here, N is equal to the band number of the image.

We can assess the classification result by making use of rule images. If necessary, reclassification can be done in terms of appointed threshold. In the rule images generated by different classification, the pixel values, which represent diverse information, will be used to build classification image. Each of these gray rule images is correspond to a region of interest or an endmember spectrum.

2.2 Endmember Projection Vector (EPV)

Each of the pixels in hyperspectral image is the approximate linear combination of endmember points in N dimensional band space:

$$p = \sum_{i=1}^{N} c_i e_i$$
$$\sum_{i=1}^{N} c_i = 1, 0 \le c_i \le 1 \qquad (3)$$

Where, N is number of endmember, c_i represents the ratio of endmember e_i in pixel p.

All the points met with the above expressions constitute a $N\text{-}1$ dimensional protruding set, with the endmembers on the vertices of the convex.

In hyperdimensional band space, each endmember can be considered to be the farthest point dissociated from the hyperplane created by others. Thus, the best separation from other endmembers will be found by producing projection on the vertical direction to the hyperplane. The endmember projection vector in hyperdimensional band space can be easily obtained by applying the endmember projection vector algorithm proposed by Geng Xiurui, *et al*. (Geng Xiurui, *et al*., 2005). Consequently, the distribution information of various surface objects in image can be gained, and the identification between the objects and the background can also be distinguished by the greatest degree.

2.3 Combining EPV And SAMC

In SAMC, only the "direction" of the spectrum is used, lacked of its "length". So, this method is not sensible to the unknown gain factor. To the identical object, all the potential brightness value will be treated with to the same. The lower pixels will be close to the origin. The "color" of a material is determined by the direction of unit vector, and the angle between vectors has nothing to do with the length as well, for the length of vector is only related to the illuminated degree of the pixel.

The result is preferable when the endmember projection vector is used to extract surface objects. However, it cannot yet to be compared with the reference spectral data acquired by empirical method. Also, the special continuity cannot be kept well. Hence, the endmember projection vector algorithm is restricted in the actual application.

On the other hand, if the SAMC is integrated with the EPV, the surface objects will be distinguished farthest, and the matching process will be done with the pre-set reference value as well, which results in better classification to the target.

3 OPERATION & RESULT

3.1 Experiment Validation

The AVIRIS data captured in the Cuprite district is used to extract information. The pseudo-colorful composition (2.1 μ m,2.2 μ m,2.3 μ m) used to handle AVIRIS data of Cuprite region is shown in figure 2. The AVIRIS is a hyperspectral instrument with high quality and low noise, including 224 bands (from 0.4 μ m to 2.5 μ m). In this experiment, the short wave infrared band – band 193 (2.2 μ m) – is chosen.

The observed reflectance (the product of true reflectance and unknown gain resulted from terrain or shadows) of AVIRIS corrected by ATREM spectrum is firstly to be classified by using SAMC. The endmembers of soil data in the spectral library is chosen, part of the observed reflectance spectrums shown in figure 3.

The result of SAMC shown in figure 4 will be achieved. Here, the black represents the unclassified objects. It can be seen from figure 4 that the best-matched pixels in the image with spectral angle between image spectrum and reference endmember spectrum fall into the same category. The pixels shown as concrete classification are depended upon the threshold of

classification image.

Fig. 2 Pseudo-colorful Composition (2.1 μ m, 2.2 μ m, 2.3 μ m)
Used To Handle AVIRIS Data of Cuprite Region
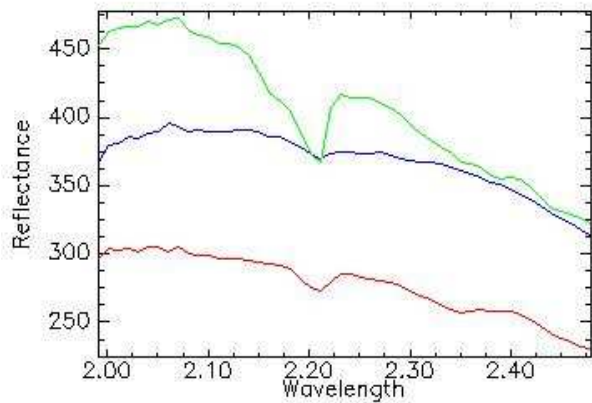(© AVIRIS Image Copyright 1995, ENVI)

Fig.3 Three Endmembers Selected From AVIRIS Spectral
Library of Cuprite Region
Red: Gray/dark brown extremely stoney coarse sandy
Green: Dark yellowish brown micaceous loam
Blue: Gray silty clay

Again, the endmember projection vector corresponding to each endmember will be obtained in the light of the different relative location of the spectral endmembers in band space. Image spectral pixels projected on the vectors, the identical or approximate objects with reference spectral endmembers will be extracted. Three different objects extracted from EPV are separately shown in figure 5, figure 6 and figure 7.
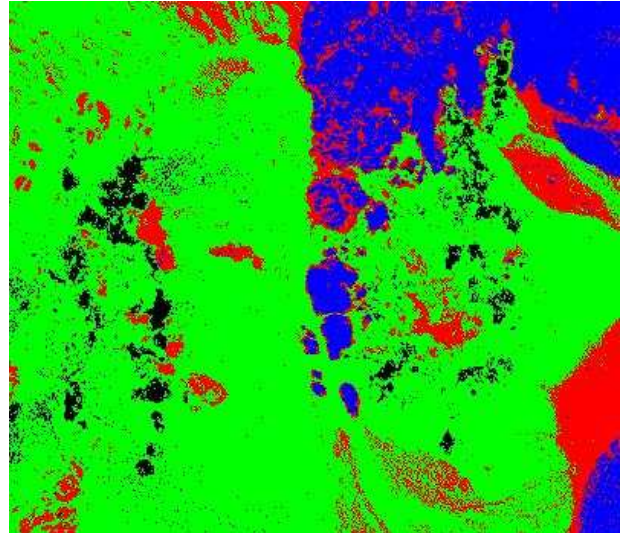
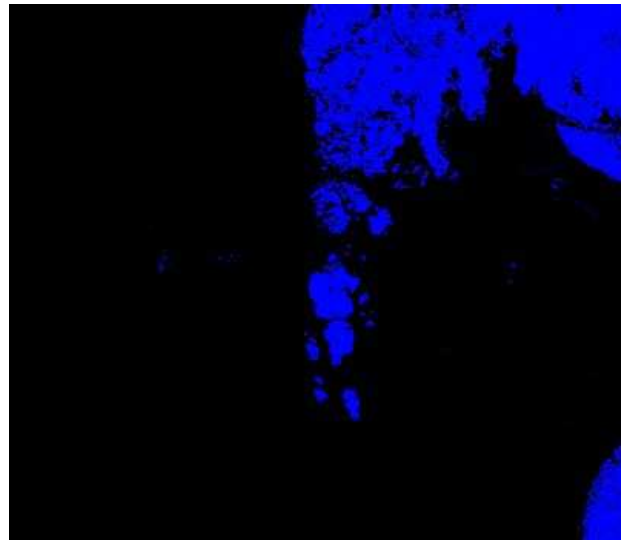Fig.4 SAMC Result in Cuprite Region

Fig.5 Object Extracted By EPV (Gray silty clay)

Fig.6 Object Extracted By EPV
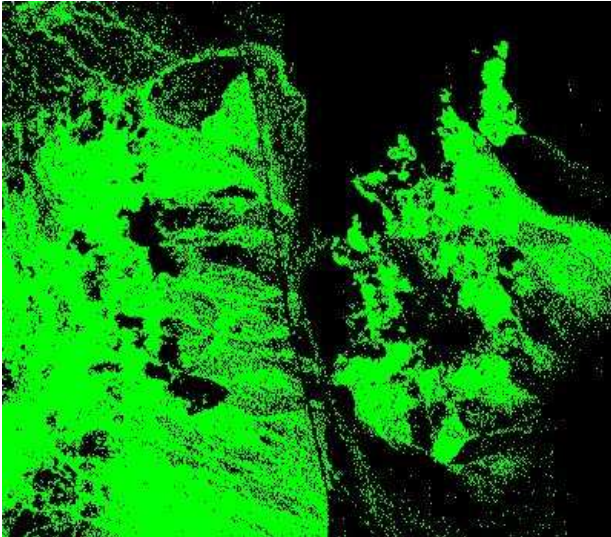(Gray/dark brown extremely stony coarse sandy)

Fig.7 Object Extracted By EPV
(Dark yellowish brown micaceous loam)

3.2 Results Analysis

In SAMC, each endmember spectrum is corresponding to a rule image, which expresses the true angle between a spectrum in the image and reference spectrum, as shown in figure 8. In rule image, the darker pixel has smaller spectral angle, which shows the spectrum of the pixel is more approximate and more matched than that of reference spectrum. Another threshold applied to rule image, new SAM classification image will be generated to attain the best classification. This is shown in figure 9.
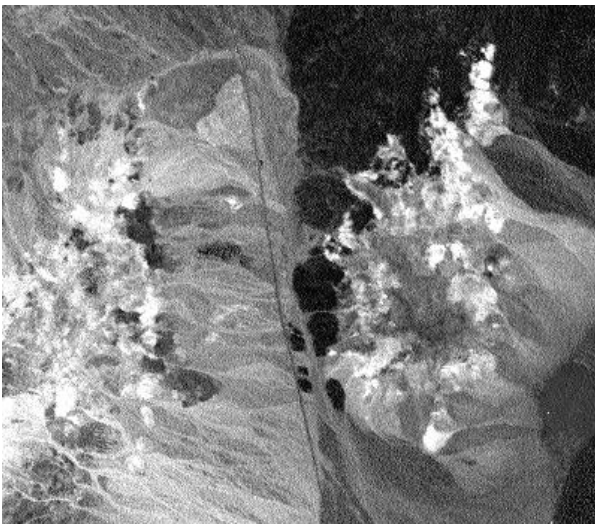

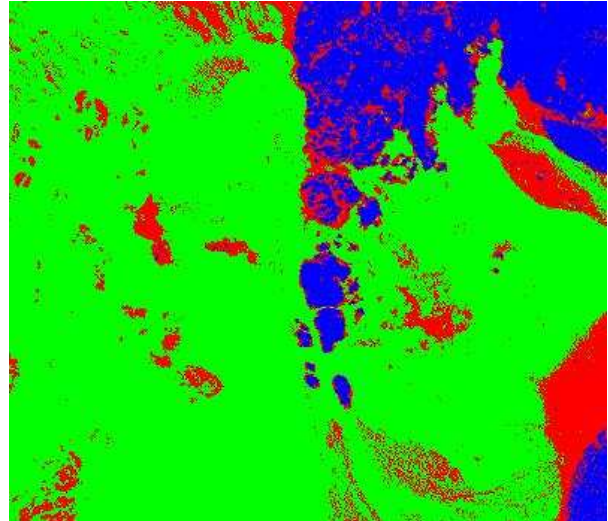Fig.8 SAMC Rule Image In Cuprite Region

Fig.9 SAMC Image After Threshold Adjustment

By using EPV, the best-matched pixels with endmember spectrum will be distinguished, and the pixel distribution involved in the SAMC image will be clearly seen as well, shown as figure 5, figure 6 and figure 7. The brightness of the pixels (shown as the color of corresponding spectral endmember) in image is in direct ratio with the content of corresponding object. There are more corresponding objects at the brighter pixels, whereas the content of the corresponding objects is less or none.

4 DISCUSSION & CONCLUSION

Spectral angle mapping classification can be used to do best match with object by calculating spectral angle to estimate the similarity between spectrums. At the same time, the consistency in space is retained. By statistic analysis, the classification precision reaches 90%.

Endmember projection vector can distinguish object corresponding to the endmembers to the best advantage. It is a good choice to differentiate surface object and its background regardless of the distribution of object information.

Combining spectral angle mapping classification and endmember projection vector can be useful to extract hyperspectral information. This technique is more accurate but has the disadvantage that further processing of the image cannot be done on the image as a whole.

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