TARGET DETECTION WITH MULTIPLE REFLECTION LINEAR UNMIXING FOR HYPERSPECTRAL REMOTE SENSING IMAGERY

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Abstract: Linear mixture model has been widely used for abundance estimation in remotely sensed imagery. Since each pixel in the remote sensing images usually covers several meters on the ground and contains more than one material, its spectrum can be considered as a mixture of all the materials residents in that pixel. Linear mixture model simply assumes this mixture is linear and then estimates the abundance fraction by least square approaches. If the surface is smooth, linear mixture can approximately fit the spectrum. However, if the surface is rough, the multiple reflection effect needs to be considered. In this study, we propose a multiple reflection linear mixture which not only consider single reflection linear mixture, but also includes double and triple reflections. In the model, we also adopt one single factor for the probability of multiple reflections or the roughness. The preliminary result shows the multiple reflection linear mixture can fit the spectrum with less error comparing to traditional linear mixture assumption.

1. INTRODUCTION

Hyperspectral imaging has been used in a broad range of applications ranging from geology, agriculture and global change to defense and law enforcement. The main reason for developing hyperspectral sensors is to improve spectral resolution of multispectral sensors so that materials which cannot be uncovered by sensor with a few spectral bands and 100-200 nm bandwidth, can be resolved by using as many as 200 contiguous bands with 10 nm spectral resolution. Therefore, one of the major challenges for hyperspectral imaging is to process this huge amount of data. On the other hand, the spatial resolutions of hyperspectral sensors are usually more than a few meters. Each pixel covers several meters on the ground and it usually contains more than one material. In this case, the mixture problem should be considered.

Linear mixture model has been widely used for remote sensing target classifications. It assumes the observed spectrum is the linear combination of all the materials resident in that pixel with corresponding abundance fractions.

This assumption performs relatively well on smooth surfaces without multiple reflection. However, it cannot compensate the nonlinearity caused by multiple reflections on rough surfaces. In this paper, a nonlinear mixture model with polynomial form to model multiple reflections is proposed. The preliminary result shows it can fit the spectrum with less error comparing to traditional linear mixture assumption.

2. LINEAR MIXTURE MODEL

Linear spectral mixing analysis is a widely used approach in remotely sensing image processing to uncover endmember residents in a pixel area [1-4]. Let $\mathbf{r}$ be an L×1 column vector and denote the spectral signature of a pixel vector in a multispectral or hyperspectral image with dimension L, i.e., the number of spectral bands. Assume that M is an L×p signature matrix denoted by $[\mathbf{m}_1\,\mathbf{m}_2\cdots\mathbf{m}_p]$, where $\mathbf{m}_j$ is an L×1 column vector representing the j-th endmember signature resident in the $\mathbf{r}$ and p is the number of present signatures. Let $\boldsymbol{\alpha}=[\alpha_1\,\alpha_2\cdots\alpha_p]^T$ be a p×1 abundance column vector associated with $\mathbf{r}$, where α_j denotes the abundance fraction of the j-th signature in the pixel $\mathbf{r}$. Then $\mathbf{r}$ can be represented as

$$\mathbf{r}=M\boldsymbol{\alpha}+\mathbf{n} \tag{1}$$

where $\boldsymbol{n}$ represents the additive noise.

Assume that M is known. Our task is to solve $\boldsymbol{\alpha}$. However, when the number of pixel vectors is greater than the number of signature p, there is no unique solution. But it can be estimated by least squares solution $\hat{\boldsymbol{\alpha}}$, which can be calculated by

$$\hat{\boldsymbol{\alpha}}_{LS}=(M^TM)^{-1}M^T\mathbf{r} \tag{2}$$

NONLINEAR MIXTURE MODEL

In nonlinear mixture model, multiple reflections are considered for the rough surface. Without losing generality, we first consider only the double reflection. Assume the electromagnetic reflected from the i-th endmember to the j-th endmember before it reached the sensor, the reflected signature is an L×1 column vector denoted as $\mathbf{m}_i\,\mathbf{m}_j$. The probability of double reflection from the i-th to the j-th endmember depends on the abundance of these two endmembers in the pixle, denoted as $\alpha_i\,\alpha_j$. The roughness of surface is presented by a scalar β which also indicates the probability of double reflection occurs. Then $\mathbf{r}$ can be represented as

$$\mathbf{r}=M\boldsymbol{\alpha}+\beta(M\boldsymbol{\alpha})^2+\mathbf{n} \tag{3}$$

where $\boldsymbol{n}$ represents the additive noise.

$$M\boldsymbol{\alpha} \approx \frac{\sqrt{4\beta\mathbf{r}+1}-1}{2\beta} = \mathbf{r}' \tag{4}$$

Then it can be estimated as follows

$$\hat{\boldsymbol{\alpha}} = (M^T M)^{-1} M^T \mathbf{r}' \tag{5}$$

3. EXPERIMENTAL RESULT

The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data to be used in the following experiment. It has 224 bands range from 0.4 μm to 2.5 μm with 10 nm spectral resolution and 20 meters spatial resolution. The image scene of 200×200 pixels shown in Fig. 1 extracted the Lunar Crater Volcanic Field in Northern Nye County, Nevada where five signatures of interest in these images are red oxidized basaltic cinders, rhyolite, playa (dry lakebed), vegetation and shade. Fig. 2 shows the classification results produced by least squares approach based on linear mixture model.

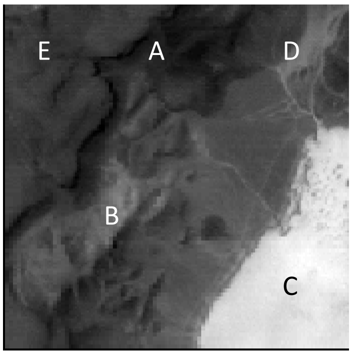
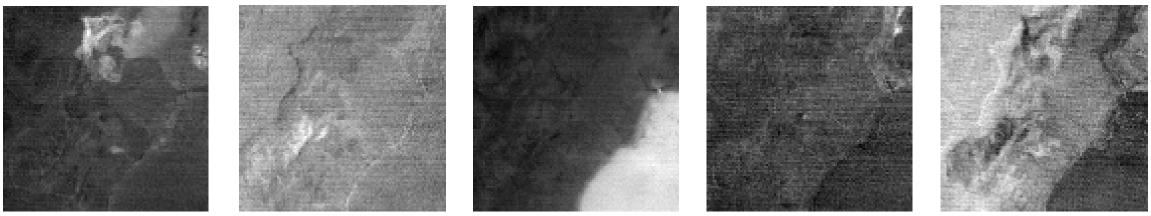


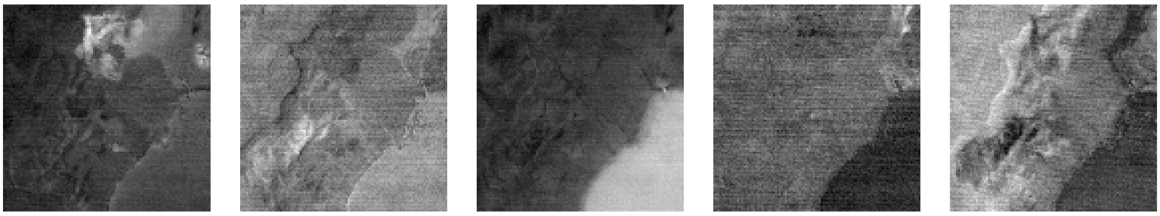
Fig. 1. An AVIRIS image scene with five signatures:
(A) cinder, (B) rhyolite (C) playa, (D) vegetation and (E) shade.



(A) cinder (B) rhyolite (C) playa (D) vegetation (E) shade

Fig. 2. Least square results for linear mixture model

When double reflection is considered, the surface roughness parameter β must be estimated. Here we perform search with step size 0.00005. It is worth noting that when β equals to 0, the model becomes linear mixture. Fig. 3 shows the classification results with β = 0.00015 on nonlinear mixture model, which is the best result with minimum number of negative abundance estimations. The number of pixels with negative abundance and their corresponding β values are shown in Fig. 4. If the β is larger than 0.0004, it performs worse than linear mixing.



(A) cinder (B) rhyolite (C) playa (D) vegetation (E) shade

Fig. 3. Nonlinear mixture model results for considering double reflection with $\beta = 0.00015$

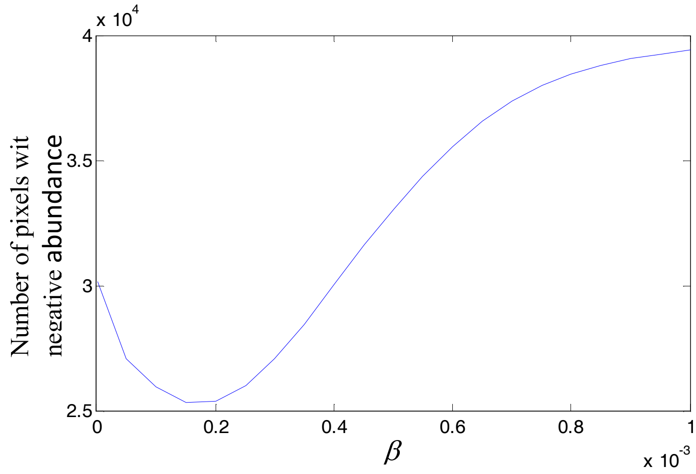


Fig 4: Number of pixels with negative abundance and their corresponding β values

4. CONCLUSION

In this paper, a new nonlinear mixture model considering multiple reflections is proposed. The preliminary result shows the improvement in reducing negative abundance estimation with considering double reflection. The result also indicates the probability of multiple reflections is very small, and β needs to be carefully selected. The algorithm may perform worse than linear mixture model if β is overestimated. In the future works, this algorithm is expected to expand to include all the multiple reflections exceed double reflections.

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