Analysis of Spectral Unmixing to Extract the Pure Pixels using Endmembers Determination Algorithms

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Abstract*- Over the past few decades linear mixing models shows a major contribution in a remote sensing field. At the time of data compilation, the linear mixing models ignore the scattering effects and secondary reflections also it expects the a priori in turn of topological and physical properties of the particular scene. In general LMM models for the spectral unmixing contain three major processes of steps which evolved in extracting the pure materials. The initial step is to calculate the number of endmembers, next step is to extract the pure spectral signature and last step is to calculate the abundance. This paper offers the view of background study in spectral unmixing. Experimented and analyzed the synthetic spectral data by applying three techniques called VCA, N-FindR and SISAL to extract the pure substances from the mixed pixel. The mean squared error for the VCA in both pure and non pure pixel assumptions are 0.00106 and computational time effort is 0.04 secs. VCA proves to be best when compared to other algorithms. Before determining the endmembers, SNR need to be estimated and HySime algorithm is used in this study to subspace the spectral data.

Keywords: LMM models, Spectral Unmixing, Endmember extraction, VCA, N-FindR

1. INTRODUCTION

Imaging spectrometer sensors store the scenes of geographical area with numerous material substances which may contain in a single pixel. Pure materials need to identify from the given mixed pixel along with the fraction of material proportions in it. If the materials are separated and identified individual materials from the mixed pixel collectively called as endmembers, a fraction of materials present in a pixel called abundances. Multispectral and hyperspectral imaging sensors derive various spectral channel pieces of information on a pixel by pixel basis. Generally, the spectral unmixing has three main stages for the end-to-end unmixing process. Hyper or ultra-imaging spectrometer contains hundreds and thousands of bands with the dimensionality [m x n x l], where m x n is the rows and columns of each band l. Each band contains hundreds of instances for different classes. To overcome this curse of dimensionality, the first stage of spectral unmixing is to reduce the scene from high to low dimensionality. The second stage is to estimate the endmembers and the third stage is to calculate the fraction of abundances (Keshava, Nirmal 2003) (Li, Jun, and José M. Bioucas-Dias 2008).

There are many approaches to unmix the spectral substances which often referred as mixed model. Fundamentally, the mixed models are categorized into two: Linear Mixing Model (LMM) and Nonlinear Mixing Model (NLMM) (Keshava, Nirmal 2003). LMM concentrates on the macroscopic scale of a pixel where the mixed pixel contains a linear mixture of materials. If the mixing materials present in microscopic scale of a pixel then NLMM techniques will be applied (Dobigeon, Nicolas, Jean-Yves Tourneret, and Chein-I. Chang 2008). This research study emphasizes on the extracting the pure substances using LMM end member extracting algorithms. The Chapter 1 discusses about the introduction of spectral unmixing and discusses about the similar research works, existing algorithms and approaches in Section 2. Section 3 describes the generic methodology framework of spectral unmixing with algorithms. Section 4 discusses about the experimental dataset and the results derived through the algorithms. Section 5 provides the conclusion and the future research work.

2. LITERATURE STUDY

Extracting the pure substances from a mixed pixel is a crucial issue over the decades. There are many extracting models implemented by research communities and shown the proven results. Unmixing the hyperspectral data with less training samples often leads to low accuracy. The semi supervised hyperspectral data are unmixed using hierarchical Bayesian model. In this study, with prior distribution of the spectral background the Bayesian model can find the relationship between two differentially expressed spectra. Also end members are determined using a reversible jump sampler, two algorithms are proposed name extended Bayesian model and hybrid metropolis-within-Gibbs algorithm. Birth, death and switch move algorithms are used to update the endmember spectra. AVRIS Moffet field and simulated spectral matrix with SNR=15 dB are experimented (Dobigeon, Nicolas, Jean-Yves Tourneret, and Chein-I. Chang 2008).

Collaborative nonnegative matrix factorization (CoNMF) is widely used in linear mixtures of the hyperspectral data which helps to estimate both endmembers and the fractional abundances. The experimental study on CoNMF is extended by including volume regularizer and new proximal alternating optimization algorithm is introduced. The extended method is referred as Robust CoNMF (R-CoNMF). The synthetic spectral dataset are generated were randomly selected from United States Geological Survey (UCGS) digital spectral library (Clark, Roger N. 2007) using LMM model with pure pixel and without pure pixel. An experimental result proves that R-CoNMF is estimating the pure substances better than the CoNMF (Li, Jun 2015).

Joint sparsity and Total-variation (JSTV) and Split-Bregman based Total Variation (SBTV) are used to elevate the presence of mixed noise in spectral data. Joint sparsity and piecewise smoothness of abundance maps were exploited in this study. JSTV proves to be best when compared to other models. These algorithms are experimented with both synthetic and real time hyperspectral images (Aggarwal, Hemant Kumar, and Angshul Majumdar 2016). Basically the computational efforts for unmixing the algorithms are complex. In (Guerra, Raúl 2015) fast algorithm for linearly unmixing (FUN) for unmixing hyperspectral data is used which adopted modified Gram-schmidt method to estimate the end members and based on orthogonal projections the fraction of abundances are calculated. AVIRIS Cuprite Image and synthetic data are used for the experimental study.

The above background study derives that LMM models are used widely for spectral unmixing which also provides high accuracy. Also the commonly used algorithms are Vertex Component analysis (VCA), N-findR, SISAL, Pixel Purity Index (PPI) (Chaudhry, Farzeen 2006) and negative matrix factorization concepts (Dobigeon, Nicolas, Jean-Yves Tourneret, and Chein-I. Chang 2008) (Li, Jun 2015) (Aggarwal, Hemant Kumar, and Angshul Majumdar 2016) (Guerra, Raúl 2015).

3. METHODOLOGY

Generally, there are three main categories of unmixing can be found in LMM paradigm. They are geometrical, statistical and sparse regression-based techniques (Li, Jun 2015). This research study focuses on estimating the end members by applying three algorithms and it is compared with evaluation metric. The algorithms used in this comparative study are N-FindR (Winter, Michael E 1999), SISAL and VCA (Nascimento, José MP, and José MB Dias 2005). This proposed methodology involved with two phases they are Dimensionality reduction using PCA and estimating endmembers in a macroscopic scale. The Fig 1 shows the methodology framework for endmembers extraction from the given spectral data.

Initially, the signal-noise-ratio SNR are computed to estimate the noise present in the spectral data. Next process is to estimate the signal subspace and project the data on it. Extract the end members using N-FindR, VCA and SISAL algorithms. In this research work HySIME (Hyperspectral Subspace Identification by Minimum Error) algorithm is used to identify and estimate the signal subspace. N-findR algorithm is a widely used approach for extracting the pure materials from a macroscopic scale. This algorithm assumes the pure materials in a pixel are present in the spectral scene. If the end members are already determined then VCA iterates the projection of data onto an orthogonal to the spanned subspace. In VCA, SVD (singular Value decomposition) is applied to reduce the sensitivity to noise which attain the better projection of a spectral data (Mauro Dalla Mura et.al). SISAL (Simplex Identification via split augmented Lagrangian) is unsupervised LMM where the assumption of pure pixel is eliminated (Bioucas-Dias, José M 2009).

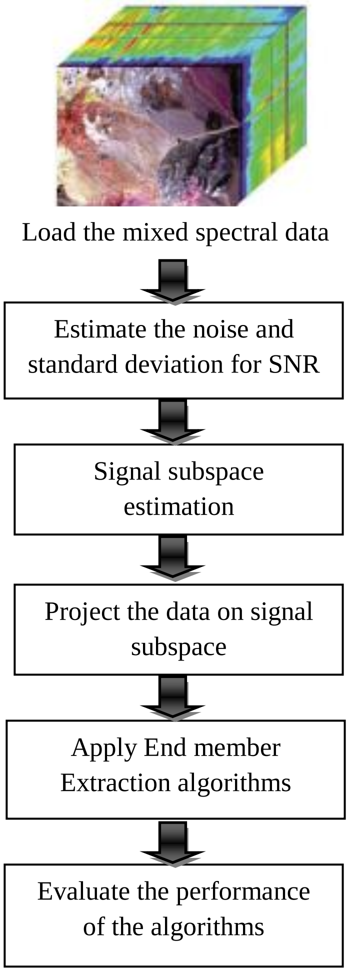
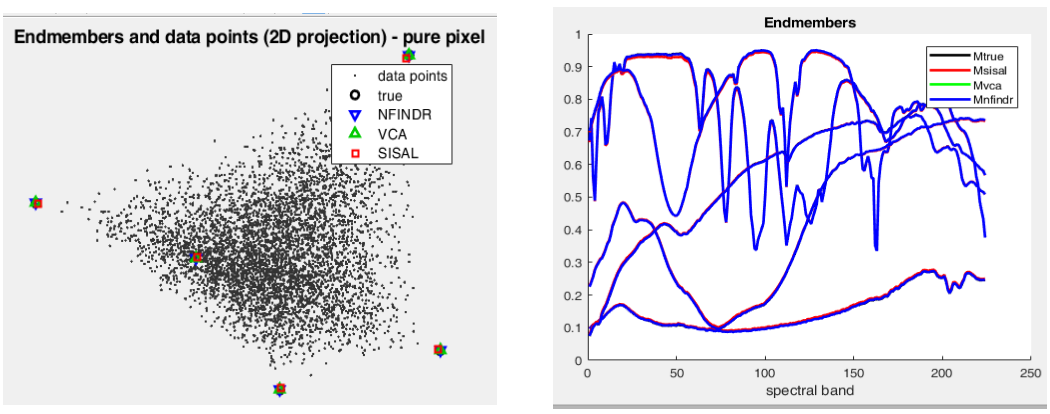


Figure 1. Methodology framework for endmembers extraction

4. RESULTS AND DISCUSSION

The synthetic dataset are experimented for this research work. SusgsP5PPSNR40 is a simulated dataset which have the pure pixels and abundances consistently distributed over the simplex and also the SNR=40 dB. It contains 224 bands with 5000 pixels [5000x224] (Bioucas-Dias, José M. 2012). This study conducts based on pure pixel and non-pure pixel assumption with endmember extraction algorithms.



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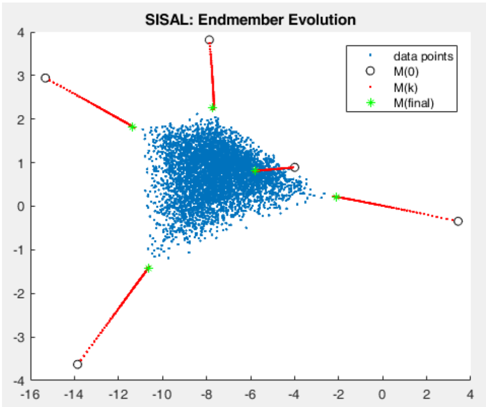

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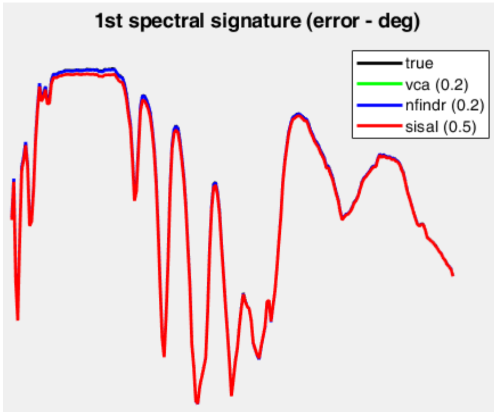
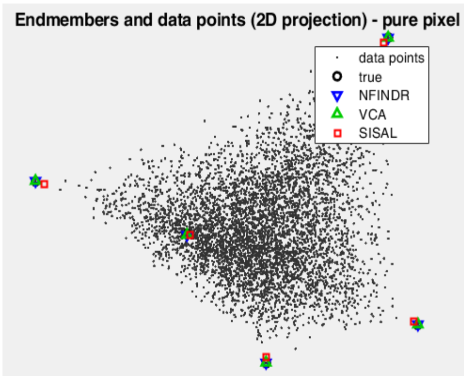
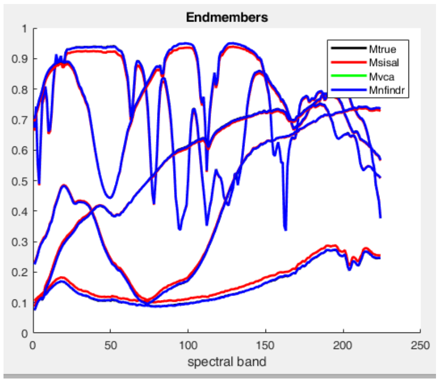


(d)

Figure 2. shows the extraction of endmembers based on pure pixel assumption a) extraction algorithm spotted a pure material which are plotted b) the identified endmembers signatures are compared with true data c) SISAL endmember evolution d) Error degree for the 1st spectral signature is compared with algorithms along with the true spectral signature



(a)



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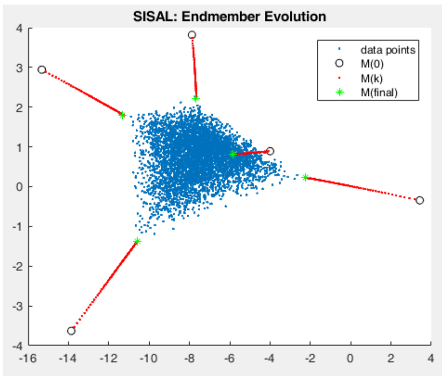

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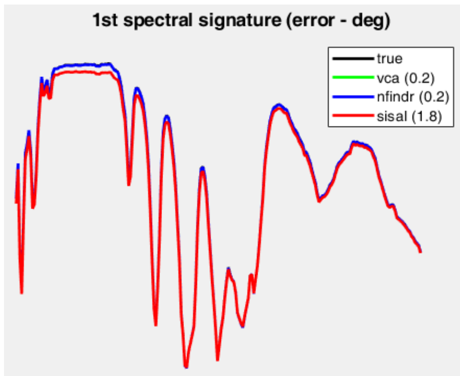

(d)

Figure 3. shows the extraction of endmembers based on non-pure pixel assumption a) extraction algorithm spotted a pure material which are plotted b) the identified endmembers signatures are compared with true data c) SISAL endmember evolution d) Error degree for the 1st spectral signature is compared with algorithms along with the true spectral signature

The SNR-SD (Standard deviation) for the five endmembers are 63.553, 41.486, 39.840, 35.397, 22.209. The minimum SNR-SD is 22.209. The Fig 2 and 3 shows the visualization the experimental results for pure pixel and non pure pixel assumption. There are 5 end members are determined in this simulated dataset. Fig 2 (a) and 3 (a) shows the pure pixel of 5 end members spotted by three algorithms VCA, N-FindR and SISAL. Fig 2 (b) and 3(b) the spectral signatures for the experimental data are compared with true scene of spectral data. Fig 2 (c) and 3 (c) endmember evolution for the SISAL which remain same for both this is due to SISAL violates the assumption of pure pixels. Fig 2 (d) and 3 (d) shows the error for the 1st spectral signature for all algorithms along with the data.

Table 1. Comparative analysis for endmember extraction algorithms

End member extraction algorithms	**Pure pixel assumption**			**Non pure pixel assumption**		
	Time taken (in secs)	**MSE**	**MAX-Error**	**Time taken (in secs)**	**MSE**	**MAX-Error**
VCA	0.04	0.00106	0.217737	0.04	0.00106	0.217737
N-FINDR	0.12	0.00106	0.217737	0.1	0.00106	0.217737
SISAL	4.74	0.00592	0.460633	5.03	0.01532	1.800585

The Table 1 shows the comparative analysis for endmember extracting algorithms based on pure and non pure pixel assumption. VCA and N-FindR shows the high accuracy when compared to the SISAL. SISAL took more computing time than the others. In either way by considering computational time and accuracy VCA offers the high and efficient to extract the endmembers for the SusgsP5PPSNR40 dataset.

5. CONCLUSION AND FUTURE WORK

Spectral unmixing is the wide domain area where many applications are involved such as subpixel detection, classification and material quantification. The widely used LMM models N-FindR, VCA and SISAL are experimented in the simulated spectral matrix dataset. N-FindR accuracy is same as VCA in accuracy of extracting endmembers but when compared to VCA the computational time taken makes the more difference. SISAL algorithm does not care the presence of pixels but still as this is unsupervised algorithm without the presence of samples it extracts the pure materials from a pixel. From the above experiment concluded that VCA offers a high accuracy with less computational time when compared to others. In future, extraction of endmembers can be hybridized and abundances are estimated with statistical hybrid model and also the real time hyperspectral data will be experimented to separate the pure substance from a pixel. This study uses LMM model with the presence of pure materials, but in reality there may not be presence of pure pixel from the spectral data. Also many materials can be involved in a microscopic scale pixel. NLMM will be used to overcome the difficulties of less sampling.

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