Application of greedy algorithhm for unmixing of hyperspectral data

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1 Abstract

Our objective for this course is to study Hyperspectral Unmixing and the different approaches that have been developed to solve this problem statemnt. In this course, we study about what is hyperspectral unmixing, its importance in real world applications and algorithms developed. We will be working on one processing technique to obtain the amount of noise in the image ie. the Signal-to-noise spectral distibution(SNR-SD) for usage of hyperspectral data. Also, we have looked into an algorithm proposed recently to solve the unmixing problem known as the Greedy Algorithm or the Greedy Sparse approximation. We will look into its code implimentation on a synthetically created image and further look into its application on real world data.

2 Introduction

Hyperspectral remote sensing, also sometimes called Imaging Spectroscopy, is used to capture data in hundreds of contiguous narrow bands of the electromagnetic spectrum. It allows whole spectral curves to be recorded with individual absorption features, therefore, providing information related to surface material that can be exploited to characterize, quantify and perform automated detection of the targets of interest with much better accuracy than multispectral or RGB image.

Modern spaceborne and airborne hyperspectral sensors measure the reflectance of the Earth's surface at hundreds of contiguous narrow bands, which results in hyperspectral image cubes with two spatial and one spectral dimension. Each pixel of a hyperspectal image is a vector that represents a spectral signature measured by the sensor. Due to low spatial resolution of the sensors and multiple scatterings, the spectra at a pixel is usually a mixture of multiple pure spectra or endmemembers, corresponding to different materials on the ground. Hyperspectral unmixing aims at identifying the endmembers in a mixed pixel and computing their fractional abundances i.e. their proportion in the pixel. Unmxing of the hyperspectral images is considered a major challenge in remote sensing data analysis.

In hyperspectral imagery, one pixel typically consists of a mixture of the reflectance spectra of several materials, where the mixture coefficients correspond to the abundances of the constituting materials. Hyperspectral unmixing refers to any process that separates the pixel spectra from a hyperspectral image into a collection of constituent spectra, or spectral signatures, called endmembers and a set of fractional abundances, one set per pixel. However, the notion of a pure material itself can be subjective and problem dependent. There are several model related to unmixing which are discussed below:

2.1 Supervised and Unsupervised Techniques

Supervised spectral un mixing relies on the prior knowledge about the reflectance patterns S of candidate surface materials, sometimes called endmembers, or expert knowledge and a series of semiautomatic steps to find the constituting materials in a particular scene. Given knowledge about the endmembers one can simply find the abundances by solving a constrained least squares problem.

The problem with such supervised techniques is that finding the correct S may require substantial user interaction and the result may be error prone, as a pixel that actually contains a mixture can be misinterpreted as a pure endmember. Another approach obtains endmembers directly from a database. This is also problematic because the actual surface material on the ground may not match the database entries, due to atmospheric absorption or other noise sources. Finding close matches is an ambiguous process as some endmembers have very similar reflectance characteristics and may match several entries in the database.

Unsupervised unmixing, in contrast, tries to identify the endmembers and mixtures directly from the observed data X without any user interaction. There are a variety of such approaches. In one approach a simplex is fit to the data distribution. The resulting vertex points of the simplex represent the desired endmembers, but this technique is very sensitive to noise as a few boundary points can potentially change the location of the simplex vertex points considerably. There are many such approaches.

2.2 Linear and Non-Linear Mixing Models

Hyperspectral unmixing refers to any process that separates the pixel spectra from a hyperspectral image into a collection of constituent spectra, or spectral signatures, called endmembers and a set of fractional abundances, one set per pixel. The endmembers are generally assumed to represent the pure materials present in the image and the set of abundances, or simply abundances, at each pixel to represent the percentage of each endmember that is present in the pixel.

Unmixing algorithms currently rely on the expected type of mixing. Mixing models can be characterized as either linear or nonlinear.Linear mixing holds when the mixing scale is macroscopic and the incident light interacts with just one material, as is the case in checkerboard type scenes. In this case,the mixing occurs within the instrument itself. It is due to the fact that the resolution of the instrument is not fine enough The light from the materials, although almost completely separated, is mixed within the measuring instrument.

Conversely, nonlinear mixing is usually due to physical interactions between the light scattered by multiple materials in the scene. These interactions can be at a classical,or multilayered, level or at a microscopic, or intimate, level. Mixing at the classical level occurs when light is scattered from one or more objects, is reflected off additional objects, and eventually is measured by hyperspectral image.

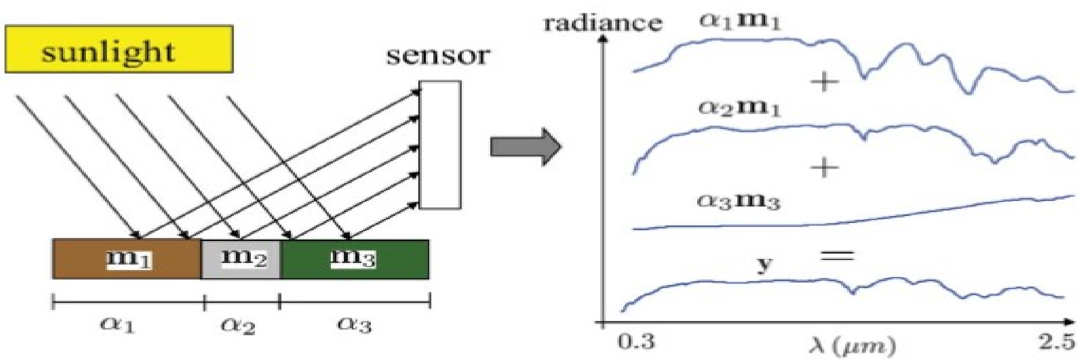

Fig. 1: Linear Unmxing, he measured radiance at a pixel is a weighted average of the radiances of the materials present at the pixel

Most of this overview is devoted to the linear mixing model. The reason is that, despite its simplicity, it is an acceptable approximation of the light scattering mechanisms in many real scenarios.

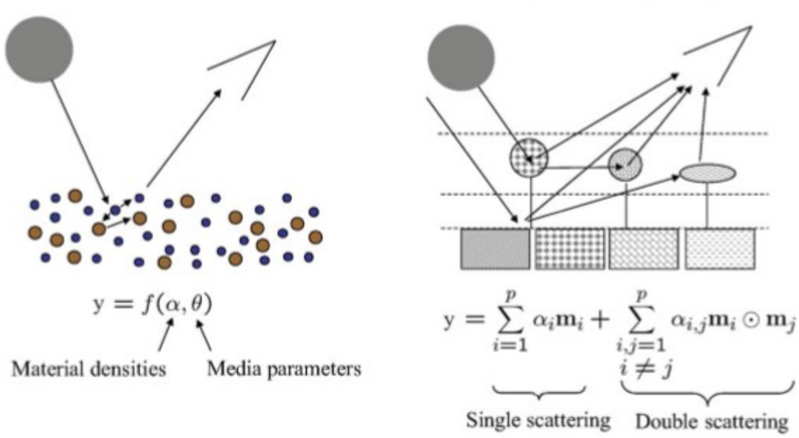

Fig. 2: Non-Linear Unmxing

3 Dataset

For the SNR-SD estimation, we have used the following datasets:

- SudP5SNR40: simulated; mixing matrix sampled from a uniformly distributed random variable in the interval $[0, 1]$
- SusgsP5SNR40: simulated; mixing matrix sampled from the United States Geological Survey (USGS) spectral library

- Rcuprite : real; subset of the well-known AVIRIS cuprite data cube 3 with size 250 lines by 191 columns by 188 bands (noisy bands were removed)

For the greedy sparse approximation:

The experiments with the synthetic data are important because they provide quantitative evaluation of the approach, which is not possible with the real-world data. In all the experiments we used a fixed dictionary, which was created from the NASA Jet Propulsion Laboratorys Advanced Space-borne Thermal Emission and Reflectance Radiometer (ASTER) spectral library (http://speclib.jpl.nasa.gov). This library contains pure spectra of 2400 materials. To perform the experiments, we selected 425 of these spectra and resampled them in the wavelength range 0.4 to $2.5\mu m$, at a constant interval of $10nm$. The resampling is performed to match the sampling strategy of the NASAs Airborne Visible and Infrared Imaging Spectrometer (AVIRIS). We dropped 24 bands of the spectra in the dictionary because of zero or very low reflectance values. This made D a 200×425 matrix. The spectra were selected such that $\mu = 0.9986$ for the dictionary. We kept $\mu < 1$ in order to ensure that the spectra in the dictionary are unique.

The synthetic hyperspecral data is simulated the with 500 mixed pixels, where each pixel was a linear combination of p randomly selected spectra from the dictionary. Following the experimental protocol, the fractional abundances of the endmembers in each pixel is drawn from a Dirichlet distribution. Therefore, the fractional abundances satisfy ASC(Abundance Sum-to-one Constraint). Gaussian white noise is then added to the data such that the pixels had $SNR = 50dB$.

4 Methodology

4.1 Linear Mixing Model

If the multiple scattering among distinct endmembers is negligible and the surface is partitioned according to the fractional abundances, then the spectrum of each pixel is well approximated by a linear mixture of endmember spectra weighted by the corresponding fractional abundances. In this case, the spectral measurement at channel $i \in \{1, \ldots, , B$ (B is the total number of channels) from a given pixel, denoted by, is given by the *Linear Mixing Model* (LMM)

$$y_i = \sum_{j=1}^{p} \rho_{ij} \alpha_j + w_i$$

where $\rho_{ij} \geq 0$ denotes the spectral measurement of endmember $j \in \{1, \ldots, , p$ at the i^{th} spectral band, $\alpha_j \geq 0$ denotes the fractional abundance of endmember j, w_i denotes an additive perturbation (e.g., noise and modeling errors), and p denotes the number of endmembers. At a given pixel, the fractional abundance α_j, as the name suggests, represents the fractional area occupied by the th endmember. Therefore, the fractional abundances are subject to the following constraints.

$$Non - Negativity \qquad \alpha_j \geq 0 \tag{1}$$

$$Sum - to - One \qquad \sum_{i}^{p} \alpha_j = 1 \tag{2}$$

4.2 Characterization of the Spectral Unmixing Inverse Problem

The Inverse Problem of finding the endmembers by a linear model is often a difficult inverse problem, because the spectral signatures tend to be strongly correlated, yielding badly-conditioned mixing matrices and, thus, HU estimates can be highly sensitive to noise. To characterize the linear HU inverse problem, we use the *Signal-to-Noise-Ratio Spectral Distribution (SNR-SD)*

$$SNR - SD(i) = \frac{\lambda_{i,x}}{e_{i,x}^T R_w e_{i,x}} \tag{3}$$

For us to obtain any valid and acceptable results, it is necessary that this ratio is $\gg 1$, else it will lead to closely spaced endmembers. If there is too much noise in the spectral response, then the unmixing does not give any proper desired results. Therefore, we must apply various correction like topographic correction, atmospheric corrections, etc. before doing any further processing like unmixing or band reduction on the image.

4.3 Greedy Sparse Approximation

A greedy algorithm is an algorithmic paradigm that follows the problem solving heuristic of making the locally optimal choice at each stage with the intent of finding a global optimum. In many problems, a greedy strategy does not usually produce an optimal solution, but nonetheless a greedy heuristic may yield locally optimal solutions that approximate a globally optimal solution in a reasonable amount of time.

Greedy algorithms approximate the signal y by iteratively selecting the atoms of the dictionary. *Dictionary* here refers to the spectral library, which is a collection of the spectral signatures of pure materials at a series of wavelengths. The word *Atom* represents here a material chosen from the spectral library. These atoms are selected such that the signal is approximated in minimum number of iterations. This greedy heuristic finally results in a sparse solution. We can unify the greedy sparse approximation algorithms under a base-line algorithm, which can be stated as the following sequential steps:

1. Identication of the atom(s) of D, best correlated to the residual vector of the current approximation of y. For initialization, y itself becomes the residual vector.
2. Augmentation of a selected subspace with the identied atom(s). The selected subspace is empty in the first iteration.
3. Residual update, after approximating y with the selected subspace.

The above steps are repeated until some stopping rule is satisfied by the algorithm. Recently proposed greedy algorithms vary in different steps of the base-line algorithms.

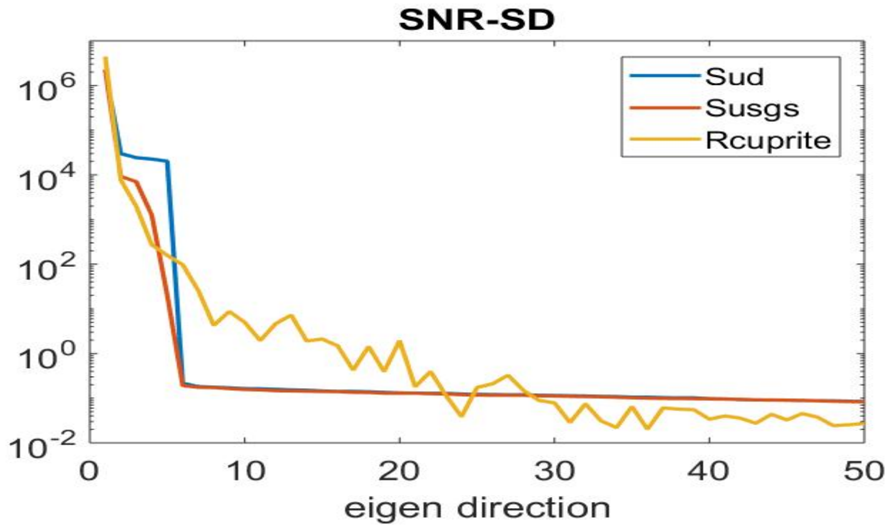

Fig. 3: Signal-to-noise-ratio spectral distribution (SNR-SD)

5 Results and Discussion

We first analyse the linear mixing model overviewed above. We review the dataset by performing characterisation of the spectral unmixing inverse problem using the SIgnal-to-Noise Spectral Distribution(SNR-SD). We do so not only on the real CUPRITE dataset of AVIRIS-NG, but we also apply it on simulated or artificially made images as listed below.

Fig. **??** plots , in the interval , for the following data sets:

- SudP5SNR40: simulated; mixing matrix sampled from a uniformly distributed random variable in the interval $[0, 1]$
- SusgsP5SNR40: simulated; mixing matrix sampled from the United States Geological Survey (USGS) spectral library
- Rcuprite : real; subset of the well-known AVIRIS cuprite data cube 3 with size 250 lines by 191 columns by 188 bands (noisy bands were removed)

From the result, we can observe that the ratio has fallen to a value less than 1 quite fast. The signal and noise correlation matrices were obtained with the algorithms and code distributed with *HySime*. From those plots, we read that, for SudP5SNR40 data set $SNR-SD(i) \gg 1$ for $i \leq 5$, thus displaying a high signal subspace.

For SusgsP5SNR40, the singular values of the mixing matrix decay faster due to the high correlation of the USGS spectra lsignatures. Never the less it is very much similar to that of SudP5SNR40 dataset.

The Rcuprite data set yields the more difficult inverse problem because has “close to convex shape” slowly approaching the value 1. This is a clear indication of a badly-conditioned inverse problem.

In the figure **??**, we can see the mixed pixel spectra which represents a synthetic image on which unmixing has to be performed. This image is made from a combination of 3 randomly selected endmembers from the spectral library. The groundtruth endmembers are shown

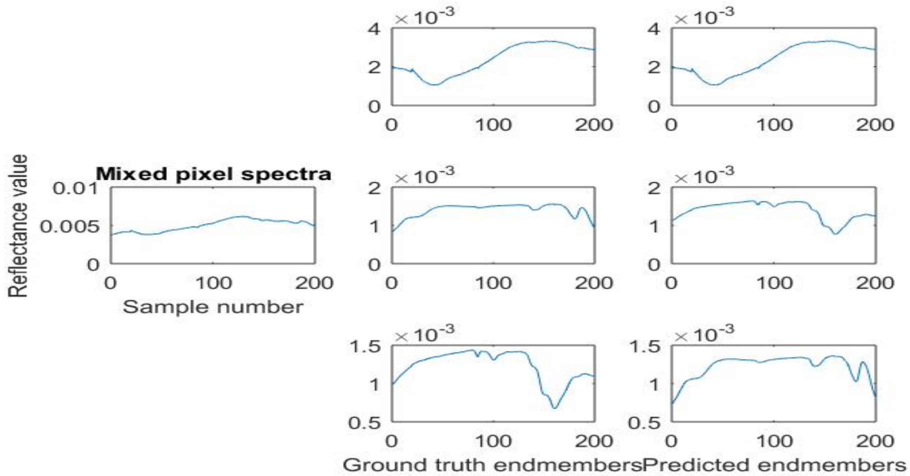

Fig. 4: Greedy Algoithm results on artificial image

in the middle column of the image. After running the greedy algorithm code, we get the predicted endmembers.

We can see that the predicted endmembers are not exactly the same as the groundtruth endmembers. This is because the greedy algorithm is an approimation method to to get the most optimised result. It has been modified to suit the problem statement of Hyperspectral Unmixing. However, there may be times when this algorithm may not yield desired results.

However, we can notice that there is not much difference between the predicted and groundtruth enmembers for this image which is a clear indication of a quite fair accuracy.

5.1 Conclusion

Hyperspectral unmixing is a challenging practical problem for unsupervised learning.The algorithm proposed by *Naveed Akhtar, Faisal Shafait and Ajmal Mian* presents a pixel based greedy sparse approximation algorithm, called SUnGP, for hyperspectral unmixing. The proposed algorithm identifies different spectra in a mixed hyperspectral pixel by iteratively selecting a subspace of spectra from a fixed dictionary and pruning it. Also, we reviewed ways to identify if the problem of linear Mixing Model (LMM) can suit a given dataset with respect to noise characteristics by analysing the Signal-to-Noise Ratio spectral distribution. The scope of this field of research is vast and unlimited. However, we limit the scope of this project to reviewing some simple proposed techniques for unmixing hyperspectral images.

5.2 Acknowledgement

I would like to acknowledge Ms. Amba Shetty for guiding me throughout the course of the project. Also, I would like to thank her for being a contant source of motivation for me to continue with this topic, which was a challenging and hard task. I would also like to thank our faculty advisor, Ms. B R Jayalekshmi, for being supportive in proceeding with the course.

title-application of greedy algorithhm for unmixing of hyperspectral data. conclsuion-how efficient algorithm is for the present dataset