ISSN : 2231-0711
Pooja Prakash Sutar | International Journal of Computer Science Engineering and Technology(IJCSET) | Dec 2014 | Vol 4, Issue 12,367-370

Hyperspectral Data Unmixing and Endmember Extraction Process Using Vertex Component Analysis Algorithm

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***Abstract*— The hyperspectral images have very huge number of pixel which stores the reflection of light beam from surface of material or object. Variations in the reflectivity of surface materials across different spectral bands provide a fundamental mechanism for understanding features in remotely-sensed multispectral hyperspectral images. Pixel in such images are mixed pixel because of its spatial resolution. A spectral unmixing is performed on mixed pixels, that contain a linear mixture of pure reflectance ground surface materials or objects called as endmember weighted by correspondent abundance fractio.**

***Keywords*— Hyperspectral Image, Spectral Unmixing, Dimensionality Reduction, Endmember, Endmember Extraction, Vertex Component analysis Introduction.**

I. INTRODUCTION

The number of Satellite's launched for Remote Sensing and Earth Observation purpose. The Satellite mounted sensor's captured data in the form of multispectral or hyperspectral images and measures electromagnetic reflection of the material within each pixel area. For any object, this data is based on the electromagnetic reflection from that particular object, absorbed by that particular object [1]. An Electromagnetic properties are varies with wavelength range (visible range – 0.4 to 0.7µm, infrared – 0.7 to 2.5µm). The satellite includes an unique capabilities to monitoring specific earth surface at low cost and in less time while actual earth surface monitoring is costly and time consuming and also it includes human error in reading ground truth.

Images are the most important source of data and information in the object detection. The use of image processing techniques has great significance for object analysis and information extraction. The Multispectral or Hyperspectral images contain number of spectral bands. Each band is measures an electromagnetic reflection of that particular object and displayed as gray scale or color (RGB) image.

Remote Sensing term related to the gathering object information about area, object characteristic and object dimension without making contact with object [4].

Spatial resolution defined as area of earth surface represented by single pixel in an image. High spatial resolution means each pixel represents a small square of earth surface [7].

Spectral Resolution is the width of region of the electromagnetic spectrum that a sensor will detect. High spectral resolution allows identification though a characterization of its wavelength spectrum [7].

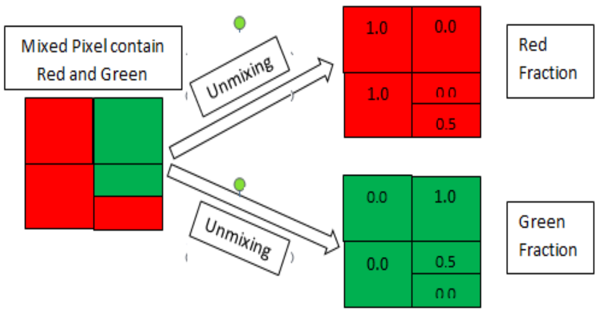

Fig. 1 – Mixed Pixel

An extraction of pure signal from the pixel is referred as Endmember Extraction Process. A common problem with such satellite images is wide existence of mixed pixels means within pixel more than one type object reflectance is present. Thus, the measured spectrum of a single pixel is a mixture of several ground cover object spectra known as endmembers, weighted by their fractional abundances. Endmember is a pure signal of an unique object or material. To utilize measured hyperspectral data, it has to decompose these mixed pixels into set of endmembers signature and weighted there fraction, indicate proportion of each endmember present in the pixel.

These process is called Spectral Unmixing or Mixed Pixel Decomposition, it involves two step: first is endmember signature computation and second is fraction of endmember in pixel estimation [5] [6]. A low numbers of spectral bands in multispectral sensors (usually a dozen or fewer) have proved sufficient to provide classification maps for large scenes with numerous applications to agriculture, forestry, oceanography, and environmental management and protection. As electro-optical remote sensing has evolved, hyperspectral sensors have been developed with hundreds of spectral bands with significantly improved spectral resolution. The ability of spectral unmixing to identify the constituent components of a pixel is a particularly important new application for these sensors [6].

II. PROBLEM STATEMENT

Problem Statement – Objects detection strategies have been changed dramatically over the past years. Any of these changes have been carried to reduce inputs and maximize benefits in real world environment.

An intensive manual ground surveys cannot keep pace (reading speed) with the land use or land coverage over large areas. Due to this reason land survey procedure become time consuming and more expensive. The calculation of crop field (green surface) helps to detect the how many hector or acre are covered by green surface (crop field). The calculation of crop field (green surface) during different season is required for understanding the intra- and inter-annual changes made on earth surface. Remotely Sensed Data is mostly used of object Detection, Estimation and Monitoring various parameter and regions. The Remotely Sensed Data provides us systematic spatial and spectral information about ground surface or earth observation. The collected information data is used for estimation and monitoring various object.

III. METHODOLOGY: VERTEX COMPONENT ANALYSIS ALGORITHM-

1.1 Spectral Unmixing:

Hyperspectral spectral unmixing is to decompose each pixel spectrum to identify and quantify the relative abundance of each endmember present in pixel [18]. Spectral Unmixing problem defined as a sequence of three stages: (1) Dimension Reduction, (2) Endmember Determination, and (3) Inversion. Some spectral unmixing algorithms first reduce the dimension of the data to minimize the corresponding computation. The goal of dimension reduction is to minimize representation of input the signal in a lower-dimensional space.

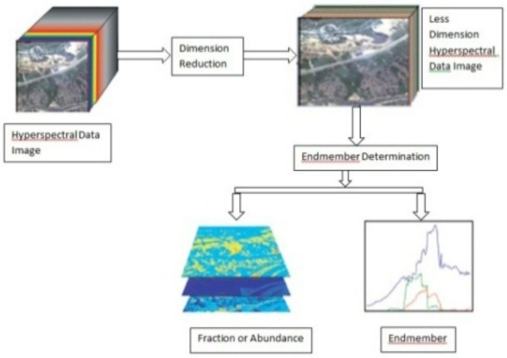

Fig. 2: Spectral Unmixing [6].

The traditional unmixing method approaches all pixels as a linear combination of pure-material spectral vectors; from this it is relatively simple to find the fractional makeup of each pixel. The end product is a set of object 0r material maps or fraction map where the value of a pixel indicates the relative abundance of an endmember. A simple four-pixel two-material example can be seen in Figure 1.

In hyperspectral Images, the maximum number of materials that can be unmixed is the number of wavelength bands in the input image, though this will not yield good results because linear unmixing forces some fraction for every endmember.

1.2 Linear Spectral Unmixing of Hyperspectral Images:

In spectral mixture model, the basic assumption is that the surface is made of a few numbers of endmembers of relatively constant spectral signature [13]. Let, R be the three dimensional $(x - axis, y - axis, number\ of\ bands)$ matrix representing the hyperspectral image data cube L is the number of spectral bands and p is the number of endmembers. Also assume that the spectrum of each pixel is a linear mixture of the spectra of p endmembers, then the original hyperspectral data shown as:

$$R = X + Noise = MS + Noise \quad \text{..(1)}$$

Where, $M = \{m(1), m(2), \dots, m(p)\}$ is the mixing matrix,

where $m(n)$ denotes the spectral signature of the n^{th} endmember.

$S = \gamma\alpha$, is the abundance of fraction matrix,

where $\alpha = \{\alpha_1, \alpha_2, \dots, \alpha_p\}^T$ abundance vector, and α is a scaling factor.

$Noise$ represents the additive noise of the hyperspectral image. Non -Negativity and Sum-To-One, these two conditions assumed on endmembers [9]. First non – negativity assumption is for mixing matrix M and abundance matrix S are need to non – negative $(\alpha \geq 0)$. Second assumption sum-to-one is for pixel fraction. Summation of all endmembers in single pixel, in every spectral band is to be one i.e.

$$\sum_{q=1}^{p} s(q) = 1 \quad \text{..(2)}$$

These two assumption are required for putting limitation on simplex formed by endmembers [9].

For geometrical simplex formation many algorithms are developed like PPI [10], n-Finder [11], VCA [12].

3.3 Dimensionality Reduction

Dimension-reduction algorithms do not reduce the dimension of data, it only reduces the computational complexity of the algorithm [6]. Principal Component Analysis (PCA) [14], Maximum – Noise Fraction (MNF) [15], Singular Value Decomposition (SVD) [16] and Orthogonal Subspace Projection (OSP) [17] are well-known projection techniques used in remote sensing. PCA, also known as Karhunen–Loéve transform, seeks the projection that best represents data in a least squares sense; MNF seeks the projection that optimizes SNR; and SVD provides the projection that best represents data in the maximum-power sense [12].

The pseudocode for the VCA is shown in algorithm 1 [12].

Algorithm 1: Vertex Component Analysis (VCA)
Input : Let Symbol, $\hat{M}$ represents mixing matrix,
$[\hat{M}]_{:,j}$ stands for j^{th} column of $\hat{M}$ and
$[\hat{M}]_{:,i:k}$ stands for i^{th} to k^{th} column of $\hat{M}$,
p stands for number of endmembers,
N stands for total number pixels,
R stands for original data,
$R = [r_1, r_2, \dots, r_N]$.
Step 1: set threshold SNR,
$SNR_{TH} = 15 + 10log_{10}(p)$.
Step 2: test whether data are to be projected onto subspace of dimension p and $p-1$.
if $SNR > SNR_{TH}$ then
Step 3
else
Step 4
end if
Step 3: $d := p$; reducing dimension to number of endmember
$U_d := RR^T/N$; where U_d is projection matrix obtained by SVD

$X := U_d^T R$;

$u := mean(X)$; where u is $1 * d$ dimension vector

$[Y]_{:,j} := [X]_{:,j} / ([X]_{:,j}^T u)$; it shows projective projection of data.

Step 4: $d := p \quad 1$;

$U_d = ([R] - \bar{r})([R] - \bar{r})^T/N$; where U_d is projection matrix obtained by PCA, where $\bar{r}$ is sample mean of $[R]_{:,i}$ for $i = 1, \dots, N$.

$[X]_{:,j} := U_d^T([R]_{:,j} - \bar{r})$;
$c := argmax_{j=1\dots N} \| [X]_{:,j} \|$; it assure that colatitude angle between u and vector $[X]_{:,j}$ is between 0° and 45° for avoiding error occure near angle 90°.
$c := [c|c| \dots |c]$; here c is a $1 * N$ vector.
$Y := \begin{bmatrix} X \\ c \end{bmatrix}$; it shows the projective projection of data using c vector.
Step 5: Let A_{p*p} is auxiliary matrix which stores the estimated endmember signatures.
$A := [e_u|0| \dots |0]$;
$e_u := [0, \dots, 0, 1]^T$;
Step 6: Assume that at least one pure pixel is present in input data R.
$for\ i := 1$ to p
$w := randn(0, I_p)$; w is a zero mean random Gaussian vector of covariance I_p
$f := \frac{(I - AA^{Inv})w}{\|(I - AA^{Inv})w\|}$;
{Each time for loop executed a vector f orthonormal to subspace spanned by the columns of auxiliary matrix A is randomly generated and y is projected onto f}
A^{Inv} stands for inverse of A.
$v := f^T Y$; v is vector which belogs to only pure pixels.
$k := argmax_{j=1,\dots,N} |[V]_{:,j}|$; finds projection extreme
$[A]_{:,i} := [Y]_{:,k}$;
$[indice]_i := k$; stores the pixel index
end for.
Step 7: $\hat{M}$ is a $L * p$ estimated mixing matrix, column contains the estimated endmember signature.
if $SNR > SNR_{TH}$ then
$\hat{M} := U_d [X]_{:,indice}$;
else
$\hat{M} := U_d [X]_{:,indice} + \bar{r}$;
end if.

IV. Review

A linear unsupervised unmixing VCA is based on the fact that endmebers are the vertices of simplex and affine transformation of simplex is also simplex. VCA assumes the presence of pure pixel in hyperspectral data and iteratively projects the data on hyper plane and form a simplex whose vertices act as endmembers. After projecting data on to selected hyper-plane, VCA algorithm projects all image pixels to a random direction and a pixel with largest projection considered as first endmember. This procedure is repeated for identifying other endmebers, which are orthogonal to subspace spanned by already estimated endmembers. According to [12] performance of VCA is better than or similar to Pixel Purity Index and N – Finder algorithm. Also, the computational complexity magnitude is lesser than other two methods.

V. Conclusion

A linear unsupervised unmixing VCA is based on the fact that endmebers are the vertices of simplex and affine transformation of simplex is also simplex. VCA assumes the presence of pure pixel in hyperspectral data and iteratively projects the data on hyper plane and form a simplex whose vertices act as endmembers. After projecting data on to selected hyper-plane, VCA algorithm projects all image pixels to a random direction and a pixel with largest projection considered as first endmember

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