An overview of Spatial-Spectral Unmixing in Satellite Imagery

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Abstract

Merging information acquired by sensor systems providing image data with different resolutions may in many cases be a valuable tool to the analyst. The multiresolution image fusion techniques merge the spatial information from a "high-resolution" image with the radiometric information from a "low-resolution" image. On the other hand, one of the physical quantities that could be acquired from remote sensing data is surface reflectance in different regions of electromagnetic reflected spectra. There are several important questions related to the spectral properties of urban materials e.g. how do those materials differ in their spectral response? what are the most suitable spectral bands for mapping urban land cover? what are the spectral limitations of current high spatial resolution remote sensing systems in terms of mapping urban land cover?, how different data fusion could be used in improving classification accuracy and urban spectral reflectance modeling? …. Almost all the urban pixels that imaged by low/medium spatial resolution sensor systems represent a composite radiance field emanating from several distinct features with different reflectance's within the sensor's field of view. Some factors like existence of mixed pixels, non-Lambertian behavior of urban and material aging, complicates urban environments. A general approach for describing land covers is using classification methods and unmixing models. One of the useful unmixing models is spectral mixture analysis in which the mixed pixel reflectance is considered as a linear summation of the reflectance and fractions corresponding to land cover types within the pixel. The aim of this study was to analyze the methods of determining spectral reflectance of important land cover materials through remote sensing data and spatial unmixing model taking in to account the variability of the land covers by using high spatial resolution and hyperspectral imagery and applications. Results show an innovation in this field.

Key words: Spatial, Spectral, Unmixing, Mixture, Multiresolution

1. Introduction

Remote sensing technologies introduce a potentially scientific basis for examining urban composition and monitoring its changes over time (Wu 2004). There are several important questions which are related to the spectral properties of urban materials such as: how do those materials differ in their spectral response; what are the most suitable spectral bands for mapping urban land cover; what are spectral limitations of current high spatial resolution remote sensor systems in terms of mapping urban land cover, how fusing different data could be used for improving classification accuracy and urban spectral reflectance modeling, etc. Due to high spatial variability of urban structure with spectrally heterogeneous materials close to each other, mixed pixels are still common in images of such areas. Other factors more complicate urban environments, including non-Lambertian behavior of urban materials that leads to high within-class spectral variability and material aging, which causes spectral changes. There are many factors introduced in the literature that demonstrate the importance of determination of urban reflectance spectral characteristics for urban materials, detailed characterization for impervious surface mapping or urban vegetation monitoring, urban material quality assessments, traffic effects on urban reflectance, growing needs for a suitable and optimum method for urban modeling, change detection and developing methods to quantify the amount of change, determination of aged and worn urban surfaces.

The objective of this paper is investigating previous research on determining urban reflectance.

2. Mixed pixel and Spectral mixture analysis

One of the major parameters in characterization of urban reflectance is the spatial resolution of the sensor. Due to higher spatial variability of phenomena in urban areas compared to sensor resolution, there are mixed pixels in low-medium spatial resolution sensor imagery. Spectral mixture analysis (SMA) provides a systematic way to quantify urban reflectance. SMA can be given by:

$$R(\lambda) = f_1 E_1(\lambda) + f_2 E_2(\lambda) + \ldots + f_n E_n(\lambda) \qquad (1)$$

R (λ) is the observed radiance; E (λ) is the spectrum corresponding to the *i*th endmember, *n* is the number of endmembers and *f* is the endmember fraction in the mixed pixel.

2.1. Determination of fraction

The objective of some urban researches is to determine endmember fraction in each mixed pixel using spectral mixture analysis. Figure 1 shows the flowchart of these approaches.

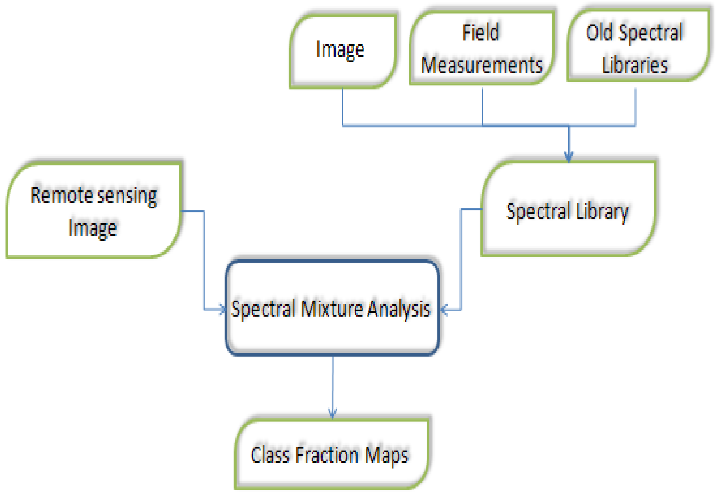

Figure1: Determination of endmember fraction within a mixed pixel using SMA.

SMA equations considering one pixel and several sensor bands can be given by:

$$\begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_m \end{bmatrix} = \begin{bmatrix} E_{11} & E_{12} & \cdots & E_{1n} \\ E_{21} & E_{22} & \cdots & E_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ E_{m1} & E_{m2} & \cdots & E_{mn} \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ fn \end{bmatrix} \qquad (2)$$

Where R, E and f are $m \times 1$, $m \times n$ and $n \times 1$ matrix, m is the number of bands (i.e. number of equations), n is the number of endmembres and number of column of E matrix and ε is model residual. The fraction of each endmember in a pixel can be calculated using least squares method in which the residual ε is minimized. The least squares method is subject to two constraints: all fractions to be nonnegative and sum of fractions to be unit.

In these approaches, designing a comprehensive spectral library is of great importance. Endmembers used in SMA can be obtained in three ways: spectroradiometer field measurements, spectral library that contains reference endmembers and from image pixels. The library collection may not successfully account for the spectral diversity of materials on the ground. Furthermore some methods of endmember extraction from image in urban environments are limited by existence of pure pixels. Usually these methods use a combination of existing methodologies for library collection. The library should remain sufficiently small so that the application of SMA remains computationally viable.

High spatial resolution, multisensor and multitemporal analysis of urban reflectance using three endmembers SMA (i.e. impervious surface, shade, vegetation) was investigated by (Small 2003), (Small 2002), (Small 2001). These analyses indicated that many urban areas can be described as a mixture of three or four spectral endmembers. In SMA-based methods (Wu 2004), (Song 2005), (Powell et al. 2007), (Franke et al. 2009), (Yang et al. 2010), normalized spectral mixture analysis (NSMA), multi endmember spectral mixture analysis (MESMA) and Bayesian spectral mixture analysis (BSMA) were studied.

In a standard application of SMA, a fixed number of representative endmembers are selected and the entire image pixels are modeled in terms of those spectral components. However, this procedure is limited because the selected endmember spectra may not effectively model all elements in the image, or a pixel may be modeled by endmembers that do not correspond to the materials located in its field of view (Powell et al. 2007). MESMA represents the spectral variation for each material in the scene. According to these studies, was concluded that normalized multiple endmember spectral mixture analysis provides more satisfying results compared to those of similar methods (Wu 2004).

2.2. Determination of class spectra

The objective of some urban researches is to determine the reflectance spectrum of the classes in each mixed pixel using spectral mixture analysis. Figure 2 shows the flowchart of these approaches.

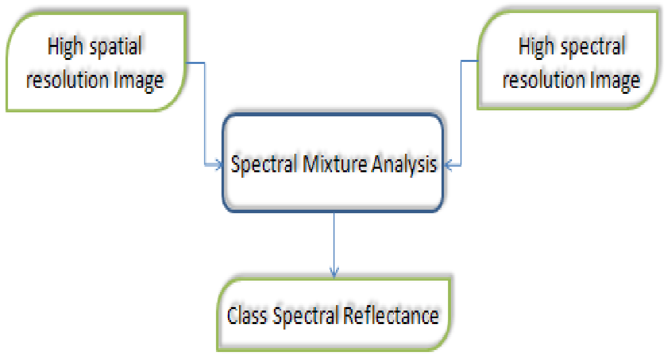

Figure2: Determination of class spectral reflectance in each mixed pixel using SMA.

For determining class spectra in one band and n pixels, eq.1 can be written as

$$\begin{bmatrix} R_{11} \\ R_{12} \\ \vdots \\ R_{1n} \end{bmatrix}_{n*1} = \begin{bmatrix} f_{11} & f_{21} & \cdots & f_{m1} \\ f_{12} & f_{22} & \cdots & f_{m2} \\ \vdots & \vdots & \vdots & \vdots \\ f_{1n} & f_{2n} & \cdots & f_{mn} \end{bmatrix}_{n*m} \begin{bmatrix} \overline{\rho}_{11} \\ \overline{\rho}_{21} \\ \vdots \\ \overline{\rho}_{m1} \end{bmatrix}_{m*1} \qquad (3)$$

Where R, f and ρ are $n\times 1$, $n\times m$ and $m\times 1$ matrix, n is the number of pixels (i.e. number of equations), m is the number of classes and the number of column of f matrix and ε is model residual. A constrained least squares method is used to retrieve spectral information (band-i radiances) for each of the class spectra (ρ). The use of a constrained method is justified, because the solution should fulfill the following two conditions: 1) the radiance values must be positive and 2) the radiance values cannot be larger than radiance saturation values of low resolution sensor. In these approaches, determining class fractions to form coefficient matrix and selecting suitable pixels are of vital importance. When high spatial resolution imagery is available, the linear mixing model can also be used to spatially unmix low resolution images. This spatial unmixing is also known as unmixing-based data fusion. In this case, the high spatial resolution data is first used to compute the fractional coverage of the different classes present in each low resolution pixel. Then, the fractions are used to look for per-pixel class endmembers.

In recent years, (Zhukov and Oertel 1999), (Zurita-Milla et al. 2009), (Mezned 2009), (Haertel and Shimabukuro 2005), (Zeng et al. 2007), (Busetto et al. 2008) used this method for determining class spectra. Subtle analysis of these works reveals that there are a few of these researches has been focused on urban environments using this method applied to very high spatial resolution images (e.g. IKONOS, QuickBird, Geoeye) and hypersepectral images. (Aidoost et al. 2013) used a new approach based on spatial unmixing (SEHR) for spectral enrichment of high spatial resolution images such as IKONOS using spectral information from Hyperion. Also, SEHR technique was applied to IKONOS panchromatic image and IKONOS multispectral image (Alidoost et al. 2012). In this research, producing surface spectral reflectance in 4 meters spatial resolution image data was successfully implemented and tested.

Having solved the aforementioned equations for all bands and all image pixels, there would be still two major problems. First, coefficient matrix (fractions matrix) may be large. Second, class variability cannot be considered (only one spectrum can be determined for each class). To overcome these problems, different solutions could be devised. A window with characteristic size in low spatial resolution image is used to consider class variability in the whole image. Then central pixel is unmixed according to neighborhood pixels. It should be noted that in this solution neighborhood size and pixel size in low resolution image is important, because it might produce large errors, which is the case dealing with urban areas. At the present stage of our investigation, it seems that integrating data such as distance, spectral similarity and texture, or using search algorithms in a neighborhood can be possible ways for selecting more suitable pixels used to determine class spectra. Weights can be calculated using spectral similarity and Euclidean distance in each window. Weighted unmixing performs better compared to un-weighted unmixing (Alidoost et al. 2013).

3. Conclusions

In this paper, we discussed the feasibility of determining class spectral reflectance in urban areas and specifically focused on using spectral mixture analysis in urban environments.

In methods of determination of endmember fraction in each mixed pixel using SMA, output is material fraction maps of study area. Using these methods different parameters such as spatial resolution of sensor, atmospheric corrections, shade effects, existence nonlinearity and choice of suitable endmember extraction algorithms should be considered.

As long as our purpose is determine class spectra in each mixed pixel using SMA, the output is high spatial-spectral resolution image form study area. In such cases, image registration, atmospheric corrections of high spectral resolution image, choice of suitable classification methods for high spatial resolution image and choice of effective pixels in equations system are key factors. Output of this method can be used for increasing classification algorithms fitness in identifying land covers, developing a spectral library of urban material, investigating the effect of urban air pollution on remote sensing data, exploring the parameters affecting urban reflectance changes and energy flows.

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