PETROLEUM EXPLORATION USING SUBPIXEL IMAGE CLASSIFICATION

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ABSTRACT: Remote sensing is an efficient tool for the assessment and monitoring of natural resources. Image classification is the most general method of information extraction through remotely sensed images. Mixed pixels, however may lead to inaccurate classification results in most conventional image classification algorithms.
Subpixel image classification is a process which tries to extract the proportions of the pure components of each mixed pixel. In traditional image classification methods which are called pixel-based methods in this article, each pixel is assigned to a single class by assuming all pixels within the image are pure. Therefore, acknowledging surface heterogeneity during image classification is important. This can be done by using spectral unmixing techniques. It is a technique that has been developed to derive fractions of spectrally pure materials that contribute to observed spectral reflectance characteristics of a mixed pixel using endmember spectra.
Image classification results is the basis of many judgments and decisions in remotely sensed projects, afterward its precision must be evaluated as well to remove any inaccuracy or errors that distorts accuracy and accurateness of process to get the process improved in further projects. There are many pixel unmixing and subpixel image classification methods however they have some common aspects in procedure. In this paper three methods of these methods are selected and applied.
Using the aforementioned method makes the process of petroleum exploration faster and to some extents easier. The best situations that this method is highly recommended are: oil exploration in very large areas to make a general decision in the process of exploration and the other situation doubtlessly is in control procedure of the petroleum exploration process.

1. INTRODUCTION

1.1 Satellite Remote Sensing For Desired Information Extraction

Satellite Remote Sensing has made information collection available where field surveying has fallen short because of prohibiting factors such cost, timing and terrain difficulties [8]. As a natural consequence, Remote Sensing science is in the process of developing models for identifying spatial patterns in a larger spatial and temporal context with relative high accuracy. The evolution of passive remote sensing has witnessed the collection of measurements with significantly greater spectral resolution. It has been motivated by a desire to extract increasingly detailed information about the material properties of pixels in a scene for both civilian and military applications. While multispectral sensing has largely succeeded at classifying whole pixels, further analysis of the constituent substances that comprise a pixel is limited by a relatively low number of spectral measurements. The recognition that pixels of interest are frequently a combination of numerous disparate components has introduced a need to quantitatively decompose, or “unmix,” these mixtures. Collecting data in hundreds of spectral bands, some sensors have demonstrated the capability of performing spectral unmixing, and they exist for one of two reasons. First, if the spatial resolution of a sensor is low enough that disparate materials can jointly occupy a single pixel, the resulting spectral measurement will be some composite of the individual spectra. This is the case for remote sensing platforms flying at a high altitude or performing wide-area surveillance, where low spatial resolution is common. Second, mixed pixels can result when distinct materials are combined into a homogeneous mixture. This circumstance can occur independent of the spatial resolution of the sensor.

1.2 Petroleum and the Keys to Exploration via Remote Sensing Data

Petroleum seepages on the earth surface and also in oceans are direct indicators of the existence of a petroleum system in seabed or deep water basins and detection of such seepages helps in minimizing the cost and risk level involved in the whole exploration process. As an illustration, detection of offshore oil seepages via satellites sensors offers a cost effective means of locating such offshore oil reserves. Such seeps are result of migration pathways of hydrocarbons where oil and gas seeping out of faults opening in the seabed are transported to the surface of land or sea. On the sea surface, due to their buoyancy in the form of thin oil films covering bubbles of gas, burst with the oil films forming oil layers on ocean surface. Using remotely sensed data is never possible, except considering seepages as mentioned such surface expressions of migration pathways of oil and gas seepages.

1.3 Spectral Unmixing For Remotely Exploration

Spectral unmixing is the procedure by which the measured spectrum of a mixed pixel is decomposed into a collection of constituent spectra, or endmembers, and a set of corresponding fractions, or abundances, that indicate the proportion of each endmember present in the pixel. Endmembers normally correspond to familiar macroscopic objects in the scene, such as water, soil, metal, vegetation or in this case "Petroleum". Generally speaking, unmixing is a special case of the generalized inverse problem that estimates parameters describing an object using an observation of a signal that has interacted with the object before arriving at the sensor [1].
The core of remote sensing and reflectance spectroscopy merged in the study of earth sciences using remotely sensed data for the

purpose of providing synoptic analysis of geophysical phenomena [4], [5]. Together, techniques for the physical modeling of terrestrial phenomena and the subtraction of atmospheric effects permitted passive multispectral and hyperspectral radiance observations to be converted to reflectance values that described the intrinsic properties of scenes independent of the observation conditions. Thereafter, geophysicists pursued model-based methods to extract physical information from remotely sensed data by representing reflectance spectra in mathematically exploitable language [6], [7]. The result was a way to not only consistently characterize and discriminate materials on the Earth's surface, but also to decompose mixtures by spectral features.

2. PIXEL UNMIXING PROCEDURE

Spectral unmixing is the decomposition of a mixed pixel into a collection of distinct spectra, or endmembers, and a set of fractional abundances that indicate the proportion of each endmember.
Whether the task is estimation of endmembers or abundances, significant attention has been focused on the computational burden of hyperspectral processing induced by the high dimensionality of the data. Some unmixing algorithms reduce the dimension of the data to sharply curtail the required computation. Not surprisingly, the familiar trade-off for less burdensome computation is decreased accuracy incurred by discarding information. We can then decompose the complete, spectral unmixing problem as a sequence of three consecutive procedures that are illustrated in Figure 2 [11]. In this figure *Endmember determination* is to estimate the set of distinct spectra (endmembers) that constitute the mixed pixels in the scene and *Inversion* is to estimate the fractional abundances of each mixed pixel from its spectrum and the endmember spectra. In the following two sections, more explanations are stated separately and try consider various approaches.

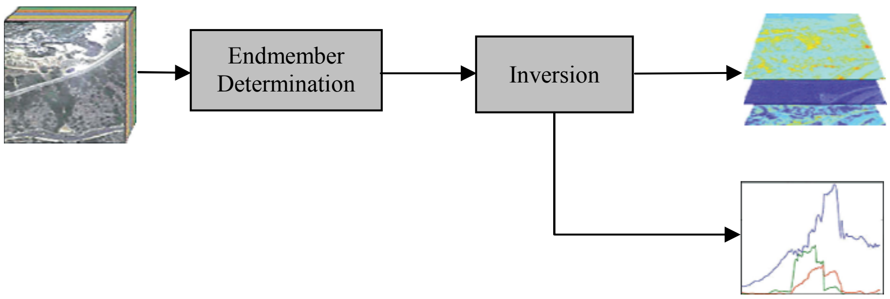

Figure 2. Spectral Unmixing Procedure Diagram

2.1 Endmember Determination

Pure features in mixed pixels are referred to as endmembers of that pixel. Selection and identification of spectral endmembers in an image is the key to success of a linear mixture model [3]. A set of endmembers should allow the description of all spectral variability for all pixels.
Two different approaches have generally been used to define endmembers in a mixing model:
♠The use of a library of reflectance spectra [1];
♠The use of purest pixels extracted from the image data itself [4].
Endmembers resulting through the first option are denoted as known endmembers where as the second option results in deriving endmembers. The maximum number of endmembers that can be derived from an image equals number of bands minus one. Typically, three to seven endmembers are appropriate for most applications, depending on the number of channels used and the spectral variability of the scene components [5]. Therefore, as no library spectra collected from field exists for this study, the second approach with the help of field reference data is adapted. So, the key to linear unmixing is to define a set of spectral endmembers that are representative of physical components on the surface and that encompass the spectral variability inherent in a given scene. To ensure the uniqueness of a solution to the LMM, the set of endmembers must be linearly independent. Along with the additivity constraint imposed, each spectral band provides a linear constraint, such that the theoretical limit to the number of endmembers in a scene is equal to the number of spectral channels plus one. However, the number of endmembers that may be practically identified and used is far fewer, typically ranging from three to seven, depending on the number of channels and the spectral variability of the scene components.

2.2 Inversion

In the previous section, we discussed endmember determination and discovered that it is often interrelated with estimating the abundance vector a, in the LMM. A key aspect of inversion is the incorporation of the dual physical constraints that a must obey, full additivity and nonnegativity. The basis for arriving at estimates is a distance metric that is minimized. As previously discussed, methods for estimating endmembers, as well as many of the statistical methods minimize some quantity related to squared-error. The same characteristic holds true for a significant majority of inversion algorithms.

3. MIXED PIXELS DECOMPOSITION

The decomposition of a mixed pixel entails the unmixing of that pixel to find the properties of its original components; usually, however, only the proportion of the area covered by each component is derived as the single property of interest. For this purpose, several methods have been developed over the last few decades. The best-known technique is linear mixture modelling, which is briefly explained is described in Section 4.1; Section 4.2 explains how this model is used to estimate a mixed pixel's proportions.

3.1 The statistical linear mixture model

The linear mixture model relates the spectral signature of a combination of a number of classes within the IFOV to the signatures of the individual classes. It was introduced by Horwitz *et al.* [10] in 1971 as a means to increase the crop area estimation accuracy achieved by standard processing techniques. They assume that a resolution cell, i.e. the ground area defined by the IFOV, contains many small objects (elements) belonging to c different classes. The spectral signature of each class i is taken to be an n-dimensional Gaussian distribution with mean m_i and variance-covariance matrix N_i, where n is equal to the number of spectral bands the scanner takes measurements at. Now suppose that a resolution cell contains elements of class i only, which are represented by random variables with mean m_i^* and variance-covariance matrix N_i^*. If the number of such elements present within the resolution cell is equal to a_i, then

$$\mathrm{m}_i = \mathrm{a}_i \mathrm{m}_i^*, \text{ and} \quad\quad (2)$$
$$\mathrm{N}_i = \mathrm{a}_i \mathrm{N}_i^*$$

provided that the variables are statistically independent. Next, assume that the proportions of the object classes within a resolution cell are defined by $\mathrm{f} = (f_1,...,f_c)^T$ and that consequently the number of elements of class i is $f_i a_i$. As a result, the composite signature of the objects will be given by:

$$\mathrm{m(f)} = \sum_{i=1}^{c} f_i \mathrm{a}_i \mathrm{m}_i^* = \sum_{i=1}^{c} f_i \mathrm{m}_i \quad\quad (3)$$
$$\mathrm{N(f)} = \sum_{i=1}^{c} f_i \mathrm{a}_i \mathrm{N}_i^* = \sum_{i=1}^{c} f_i \mathrm{N}_i$$

The latter equation only holds if the random variables associated with elements from different classes are statistically independent as well. Assuming that the conditions for the central limit theorem are satisfied, we can consider Equation (3) as the mean vector and variance-covariance matrix respectively, of a distribution that is multivariate normal (see Figure 3). Thus, the composite signature of a combination of classes can be described in terms of the signatures of the individual classes.
The validity of the linear mixture model depends on the type of application. As described in the previous paragraph, the model is based on the assumption that the random variables associated with the elements are statistically independent. With regards to ground cover applications, Settle and Drake [9] translate this prerequisite to the condition that the amount of multiple scattering between the different ground cover types must be negligible, i.e. (nearly) all photons reaching the scanner's sensor have interacted with just one cover type. According to Campbell [19], this situation arises when the resolution cell contains two or more surfaces occurring in patches that are large relative to the sensor's resolution. On the other hand, if the component surfaces occur in highly dispersed patterns, mixing is likely to be nonlinear since the probability that radiation is scattered by one cover type and subsequently reflected by another cover type before arriving at the sensor is much higher.

3.2 Decomposition based on the statistical model

Mixed pixels can be decomposed by inverting the statistical model described previously. To this end, the linear mixture model is usually rewritten in matrix-vector notation:

$$\mathrm{x} = \mathrm{Mf} + \mathrm{e} \quad\quad (4)$$

If the number of spectral bands and ground cover types are given again by n and c respectively, then x represents an n×1 pixel vector or multispectral observation, while, as before, f denotes the c×1 fractions vector with the proportions of the different ground cover types. Each column of (n×c) matrix M contains the spectrum of a so-called endmember, which is the reflectance typical for a resolution cell containing nothing but the cover type of interest. According to Section 4.1, the i-th endmember spectrum is equal to the mean vector mi of class i, but there exist some other views as well. The mixing equations defined by Equation (4) are usually accompanied by two constraints that are obvious in the model of Section 4.1, but which should be satisfied explicitly when estimating f. The sum-to-one constraint is that a pixel is well-defined by its components, whose proportions should therefore add up to unity:

$$\sum_{i=1}^{c} f_i = 1 \quad\quad (5)$$

The other constraint that should be satisfied is the positivity constraint, which says that no component of a mixed pixel can make a negative contribution:

$$f_i \geq 0 \text{ for } i = 1,\ldots,c \quad\quad (6)$$

Satisfaction of the latter constraint is often difficult and may require some specialised techniques. Together, the mixing equations and the constraints describe a model that must be solved for each mixed pixel that is to be decomposed, i.e. given x and M, one has to determine f and e subject to (4)-(6).

An important characteristic of a decomposition method is the criterion that determines which solution of the linear mixture model is optimal. Suppose that all endmember spectra are linearly independent of each other and consider the system of equations defined by Equations (4) and (5) (note that (6) is an inequality and not an equation). If the error vector e is disregarded, then this system of n+1 linear equations in c unknowns(the f_i), has infinitely many solutions if c>n+1, exactly one solution if c=n+1, and at most one solution if c<n+1. To provide a general solution in the last case, error vectors unequal to zero have to be allowed, which results in an infinity of solutions again (c+n>n+1). In contrast to the previous underdetermined system (c>n+1), however, it is possible to identify a solution that is optimal in some sense based on the value of the error vector e. The solution that is selected following the popular maximum likelihood approach is the combination of fractions and error vector that has the highest probability. Since e is assumed to have a multivariate normal distribution with a zero mean and variance-covariance matrix N(f), the most probable solution is the one that minimises

$$\begin{aligned} & \mathrm{e}^T (\mathrm{N(f)})^{-1} e + \ln|\mathrm{N(f)}| = \\ & (\mathrm{x} - \mathrm{Mf})^T (\mathrm{N(f)})^{-1} (\mathrm{x} - \mathrm{Mf}) + \ln|\mathrm{N(f)}| \end{aligned} \tag{7}$$

In this equation, ln|N(f)| denotes the natural logarithm of the determinant of N(f), while the other term represents the Mahalanobis distance between pixel x and point Mf. Thus, among the infinitely many solutions for the linear mixture model, the maximum likelihood approach is able to identify the single, most probable alternative. Although the maximum likelihood criterion determines which of the solutions is more probable, it does not say how these solutions can be found. Basically, there are two ways to solve the equations of the linear mixture model: brute force and mathematical analysis.

Brute force approximation, The brute force approach is conceptually the least complex as it simply searches the entire solution space. For every f that satisfies the sum-to-one and positivity constraint, the corresponding error vector e and variance-covariance matrix N(f) are calculated, and Equation (7) is evaluated; the f that minimises this cost function is taken as the fractions vector of x. Obviously, this approach leads to an approximation of the optimal f because the solution space is searched taking discrete steps. Furthermore, it has a considerable computational complexity: if the sampling rate, which equals the reciprocal of the step size, is denoted by r, the maximum likelihood criterion has to be evaluated in the order of r^{c-1} times. By varying the sampling rate, the accuracy of the approximation can be traded off against computational costs.

The brute force approach is to apply systematic sampling of this simplex in order to determine the point p that is closest to pixel x. The proportions vector corresponding to p is subsequently adopted as the proportions vector of x.

Analytic approximation, Finding the minimum of the maximum likelihood cost function using mathematical analysis is difficult because the variance-covariance matrix N(f) depends on the fractions vector. However, if all matrices N_i are equal to a common matrix N, then a closed expression can be derived. Fortunately, as Horwitz *et al.* convincingly argued [51], N(f) can be approximated by the mean variance-covariance matrix

$$\mathrm{N} = \frac{1}{\mathrm{c}} \sum_{i=1}^{c} \mathrm{N}_i \tag{8}$$

without much loss of accuracy, as long as the dispersion of the endmembers is relatively large compared to the within-class variation of the individual ground cover types. Now the minimum of Equation (7) can be calculated by setting the partial derivatives with respect to each f_i to zero, which gives the unconstrained estimator

$$\hat{\mathrm{f}}_0 = \mathrm{UM}^{\mathrm{T}}\mathrm{N}^{-1}\mathrm{x} \quad \text{where} \quad \mathrm{U} = (\mathrm{M}^{\mathrm{T}}\mathrm{N}^{-1}\mathrm{M})^{-1} \tag{9}$$

If the sum-to-one constraint is imposed, then a standard Lagrangian analysis gives a slightly different solution (Settle and Drake [99]):

$$\hat{\mathrm{f}} = \hat{\mathrm{f}}_0 + \alpha\left(1 - l^{\mathrm{T}}\hat{\mathrm{f}}_0\right)\mathrm{U}l \quad \text{where} \quad \alpha = (l^{\mathrm{T}}\mathrm{U}l)^{-1} \tag{10}$$

and l denotes the (c×1) vector consisting entirely of ones. Satisfaction of the positivity constraint cannot be achieved with a similar transformation, but requires some post-processing of the initial estimate or an alternative approach to solve the model's equations. The simplest post-processing approach is to set any negative proportions to zero and renormalize the fractions vector. Although this method may cause some extra loss of accuracy, the computational costs are so low that it is often applied. Together, the simple matrix-vector operations of Equation (10) and the fast renormalisation method provide a near-optimal solution of the linear mixture model that can be calculated efficiently.

4. CONCLUSIONS

Detection of offshore oil seepages or the ones on the land surface, via satellite imagery offers a cost effective means of locating such oil reserves. Seepages of petroleum are result of migration pathways of this substance out of faults opening in the on the land or on the seabed which are transported to the surface of the sea. Using remotely sensed data is never possible, except considering seepages as mentioned such surface expressions of migration pathways of oil and gas seepages.

Spectral unmixing using remotely sensed data represents a significant step in the evolution of remote decompositional analysis. It is a consequence of collecting data in greater and greater quantities and the desire to extract more detailed information about the material composition of surfaces. Linear mixing is the key assumption that has permitted well-known algorithms to be adapted to the unmixing problem. In fact, the resemblance of the linear mixing model to system models in other areas has permitted a significant legacy of algorithms from a wide range of applications to be adapted to unmixing. However, it is still unclear whether the assumption of linearity is sufficient to model the mixing process in every application of interest. It is clear, however, that the applicability of models and techniques is highly dependent on the variety of circumstances and factors that give rise to mixed pixels.

The outputs of spectral unmixing, endmember, and abundance estimates are important for identifying the material composition of mixtures. Unmixing is a close relative to another important problem in image spectral processing, the subpixel target detection problem. Mixtures, however, are not limited to simple terrestrial components such petroleum seepages. Ever-growing spectral libraries that reduce the dependence on in situ determinations of endmembers have aided these efforts. Nevertheless, the pursuit of increasingly accurate and precise knowledge from remote sensors puts spectral unmixing on the forefront of future remote sensing missions and research endeavours.

Further experiments will surely continue to investigate unmixing in greater depth.

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