Material Classification of Hyperspectral Images using Unsupervised Fuzzy Clustering Methods

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Abstract

This paper presents a novel approach in classifying materials in Hyperspectral images. In particular, unlike other similar approaches in which every pixel in the image is mapped to one of the reference spectra, the proposed methods use the data itself to create clusters of pixels with the same material. This is done by using unsupervised fuzzy clustering methods. Here, two fuzzy clustering approaches have been addressed: Fuzzy C-Means clustering (FCM) and Fuzzy Relational Clustering (FRC). The proposed methods can also solve the problem of identifying the objects for which the radiance of light makes it barely hard to identify them as a single object e.g., a pitched roof. The proposed methods have been applied on the CASI image and the results show that they can successfully classify the materials in the image.

1. Introduction

Hyperspectral images provide a rich source of raw data to analyze land cover information. In particular, they collect image data simultaneously in several spectral bands making it possible to derive a continuous spectrum for each image cell. Therefore, each image cell, pixel, is a vector of n different values each representing a different spectral band. Identification of objects and materials can be done by analyzing such image.

Pattern recognition and remotely sensed data analysis have been the subject of intensive research [1]. The emerging techniques and particularly statistical methods are well adapted for hyperspectral images [2]. Most approaches to analyzing hyperspectral images attempt to match each image spectrum individually to one of the reference spectra, signatures, in the spectral library, the matching signature must be ranked using some measure of goodness of fit, with the best match designated the “winner”. Consequently, a similarity measure has to be defined to compare images. Euclidean and SAM distance are among the frequently used measures in the literature [3].

In order to directly compare a pixel with a signature, the encoded radiance values in the pixel must be converted to reflectance. Various methods are proposed for modeling spectral reflectance in order to omit the radiance effect in the image [4, 5]. The action of assigning a pixel to the most similar signature is called material mapping [4]. Various algorithms have been developed to address material mapping in hyperspectral images [1, 2, 6-11].

However, In addition to surface reflectance, the spectral radiance measured by a remote sensor depends on the spectrum of the input solar energy, interactions of this energy during its downward and upward passages through the atmosphere, the geometry of illumination for individual areas on the ground, and characteristics of the sensor system [4]. These additional factors not only affect the ability to retrieve accurate spectral reflectance values for ground features, but also introduce additional within-scene variability which hampers comparisons between individual image cells.

The problem of converting the radiance values in a pixel into the signatures can be relieved by using unsupervised clustering of pixels. Specifically, the data in an image can be compared to one another and form clusters. As a result, there is no need to compare a pixel to a signature.

Here, several unsupervised fuzzy clustering techniques are proposed to classify materials with regards only to the image data not to signatures. Since the proposed methods do not compare pixels to signatures, there is no need to explicitly convert the radiance values to reflectance. Besides, the proposed methods can solve the problem of identifying the objects for which the radiance of light makes it barely hard to identify them as a single object e.g., a pitched roof. Here, methods that can classify a pitched roof as a single object are also presented.

The remainder of this paper is organized as follows. Section 2 reviews the problem of radiance in material classification. Section 3 and 4 provide a description of Fuzzy C-Means Clustering (FCM) and Fuzzy Relational Clustering (FRC), respectively. Section 5 reports the experiments conducted to evaluate the performance of the proposed method. Finally, concluding remarks are presented in Section 6.

2. Problem of Radiance

The image data itself does not bear much resemblance to the signatures in the reflectance spectra library. The spectral radiance measured by a remote sensor depends on the spectrum of the input solar energy, interactions of this energy during its downward and upward passages through the atmosphere, the geometry of illumination for individual areas on the ground, and characteristics of the sensor system [4].

In a non-flat train, the energy received varies instantaneously across a scene because of differences in slope angle and direction. The amount of illumination received by an area can also be reduced by shadows. Pitched roofs are vivid examples of this condition (See Fig.1). As a result, most of the algorithms are unable to identify a pitched roof as a single object.

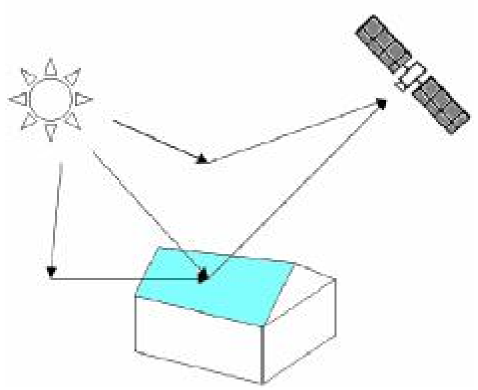


Fig. 1. The Effect of Radiance

3. Fuzzy C-Means Clustering

FCM is a well known clustering algorithm that allows one piece of data to belong to more than one cluster. Let $X=\{x_1, x_2,..., x_n\}$ be a set of data which is composed of $c=\{v_1, v_2,..., v_c\}$ different classes, then FCM can be seen as a strategy for minimizing the following objective function:

$$J(U, v_1, v_2,..., v_c)=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^m D_{ij}^2 \quad (1)$$

Under the constraints:

$$\sum_{i=1}^{c}u_{ij}=1, \forall j=1,...,n \quad (2)$$

where $u_{ij}\in[0,1]$ indicates the membership of data x_i to cluster v_j - the *jth* centroid of c and D_{ij} is the distance between data vector x_i and centroid v_j. A variety of distance functions to measure D_{ij} have been used.

Parameter $m\in[1,\infty)$ is called fuzzifier, which is used to control how much clusters are allowed to overlap. m is usually set to 2.

FCM is carried out through an iterative optimization of the objective function as shown in equation (1).

Different distance functions have been introduced and used to calculate the distance or similarity between two vectors. Selecting an appropriate distance function is a problem-oriented task and usually is done by an expert. Here, Euclidean distance function measured by:

$$D_{ik}=\| x_k - v_i \|^2 \quad (3)$$

and cosine distance functions which is defined as:

$$D_{ik}=1-\cos(x_k, v_i) \quad (4)$$

where

$$\cos(u,v)=\frac{u.v}{\|u\|\|v\|} \quad (5)$$

have been used as distance functions in experiments. Spectral Angle Mapper (SAM) and cosine distance are used interchangeably in this paper.

According to Bezdek's theorem [12], objective function may fall in local minimum if v_j and u_{ij} are updated in each iteration by the following equations:

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{D_{ik}}{D_{jk}} \right)^{\frac{2}{m-1}}} \quad (6)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}} \quad (7)$$

Using cosine function leads to the same rule for u_{ij} and following update rule for v_j:

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} \ x_k}{\sum_{k=1}^{n} u_{ik} x_k v_i} \quad (8)$$

4. Fuzzy Relational Clustering

Traditional fuzzy relational clustering (FRC) can be summarized as follows [13]:

1. Determine the set of samples to be clustered. Again, Let $X = \{x_1, x_2, ..., x_m\}$ be a set of data where x_i is a $1 \times N$ vector with real values.
2. Establish the fuzzy similarity matrix: to construct the fuzzy similarity matrix R, the first step is to calculate the similarity indices $r_{ij} = R(x_i, x_j)$ of x_i and x_j where r_{ij} can be any arbitrary similarity function. Then, the similarity matrix can be obtained as follows:

$$\mathbf{R} = \begin{pmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & & \vdots \\ r_{m1} & \cdots & r_{mm} \end{pmatrix}$$

3. Transform fuzzy similarity matrix, **R**, into a fuzzy equivalence matrix, $\mathbf{R}^*$=matrix $(r_{ij}^*)_{i,j=1..m}$: A fuzzy similarity matrix of size $m \times m$ should be composed by itself at most $m-1$ times to be converted to a fuzzy equivalence matrix.
4. Calculate λ-cut matrix of $\mathbf{R}^*$. The λ-cut matrix $R_l^* = (r_{ij}^l)_{m \times m}$ can be defined as follows:

$$r_{ij}^l = \begin{cases} 1 & r_{ij}^* \geq l \\ 0 & r_{ij}^* < l \end{cases}$$

where $l \in [0,1]$ is a pre-determined threshold. Similar rows of matrix R_l^* form a cluster. With an equivalent matrix and different thresholds, different clustering results will be obtained. The selection of λ impacts the number of clusters directly; the smaller values of λ, the smaller number of clusters. In two special cases, λ =0, 1 the results is 1, m clusters, respectively.

However, in the case of hyper-spectral images with high dimensions, fuzzy equivalence matrix calculation is computationally too complex to be considered practically. This problem can be solved by finding connected components in an undirected graph [14]. Consider an illustrative example. Let $X = \{x_1, x_2, x_3, x_4, x_5\}$ be the set of data and the similarity matrix, $\mathbf{R}$, is described as follows,

$$R = \begin{bmatrix} 1 & 0.1 & 0.8 & 0.5 & 0.3 \\ 0.1 & 1 & 0.1 & 0.2 & 0.6 \\ 0.8 & 0.1 & 1 & 0.3 & 0.1 \\ 0.5 & 0.2 & 0.3 & 1 & 0.6 \\ 0.3 & 0.6 & 0.1 & 0.6 & 1 \end{bmatrix} \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{matrix}$$

Fig.2 shows the corresponding graph, G, of the similarity matrix.

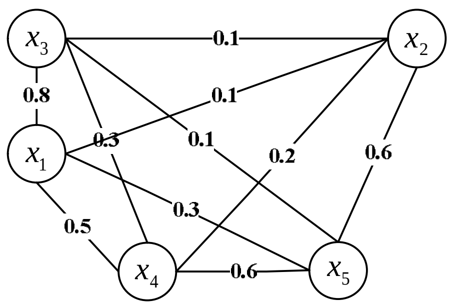


Fig. 2. Example of fuzzy relation matrix and complete graph

Assume that L^k is the *k-th* path between two vertices x_i and x_j. Define $S(L^k)$ as the minimum of edge weights involved in L^k. Then, r_{ij}^* is the maximum of values of S for all paths between x_i and x_j. Therefore, after l -cut if minimum edge-weights in each path between x_i and x_j are less than l then $r_{ij}^l = 0$; Consequently, x_i and x_j belong to different clusters.

Let G^l be l -cut graph of G. There is no edge between x_i and x_j if their edge-weight is less than l . $r_{ij}^l = 1$ if and only if x_i and x_j are in the same connected component of G^l. Therefore, every connected components of G^l construct the fuzzy equivalence relation. The connected components of G^l is the result of clustering. For $l = 0.5$, G^l is represented in Fig. 3. For G^l, two clusters can be derive: $A=\{x_1,x_3\}$, $B=\{x_2,x_4,x_5\}$.

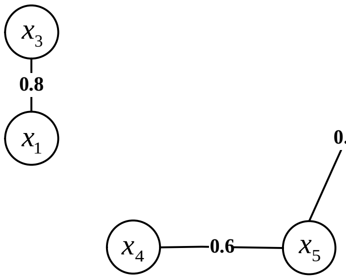


Fig. 3. Example of l -cut graph

5. Experiments

In this section a comparative study of FCM and Relational clustering using real hyperspectral data is presented. The above mentioned methods are applied to real hyperspectral data collected by CASI (Compact Airborne Spectrographic Image) system.

5.1. Dataset Description and Experiment Design

In this study, different experiments are performed on the CASI image (Fig. 4). The number of bands for this image is fixed to 32 channels and the spatial resolution of the image is 2m. The proposed algorithms have been applied to both original image and its derivative which is defined as follows:

$$dX=[x_2-x_1, x_3-x_2, \mathbf{K}, x_n-x_{n-1}]$$

where $X=[x_1,x_2,\mathbf{K},x_n]$ is a hyperspectral vector and n is the dimension of sample data.

Table 1 summarizes the algorithms and parameters used in each experiment.

Table 1. List of Experimnts

Algorithm	Input	Similarity Measure
FCM	hyperspectral data	Euclidean distance
FCM	hyperspectral data	cosine distance
FCM	derivative of hyperspectral data	Euclidean distance
FCM	derivative of hyperspectral data	cosine distance
FRC	hyperspectral data	cosine distance
FRC	derivative of hyperspectral data	cosine distance

5.2. Results and Discussion

The above experiments have been done on the CASI image described in the previous subsection. As shown in Fig. 5, fuzzy relational clustering and FCM (using cosine distance) identified pitched roofs as a single object while traditional FCM clustered the largest pitched roof into 3 clusters. The reason is that using Cosine distance function omits the magnitude of pixel values and result in comparing each pixel relatively to other pixels in an image. Therefore, using Cosine distance function reduces the effect of illumination of the targets.


Fig. 4. The original CASI32 image.

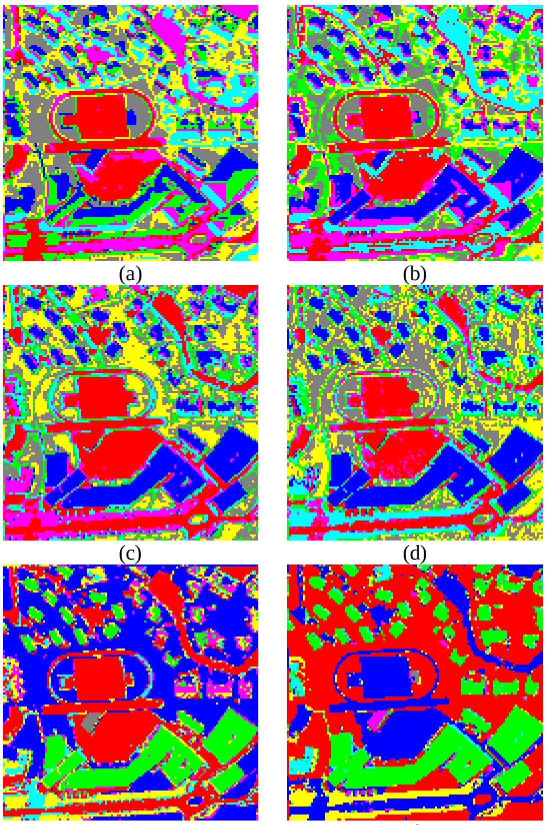
Clustering derivatives of hyperspectral data shows higher performance in reducing the effect of radiance. FCM on the original data clustered pitched roofs in 3 clusters (Fig.5 (a)) while applying the same algorithm on the derivatives of data results in 2 clusters Fig.5 (b). The same fact is true for the case of relational clustering (Fig.5 (d) and Fig.5 (e) accordingly). It is due to the fact that the derivation makes each value of a hyperspectral vector relative to other values in the vector. In addition to using the derivation of data, normalizing hyperspectral vectors can also be used to make the values relative to one another.

Fuzzy relational clustering, as shown in Fig. 5(e) and Fig. 5 (f), performs much better than any variation of FCM, The reason is that it does not use randomly chosen cluster centers at the beginning phase of the algorithm. In contrast to FCM, the fuzzy relational clustering methods determine the centers of clusters when the algorithm is finished. Furthermore, the fuzzy relational clustering does not need a pre-determined number of clusters. In particular, by choosing different values for λ, different number of clusters and different cluster shapes may be acquired. Last but not least, it's worth noting that clusters resulted from applying FCM have hyperspherical shapes which may not be the case in many problems while clusters resulted from applying Fuzzy relational clustering do not have such restriction.

6. Conclusion

In this paper, the problem of classification of hyperspectral images has been addressed. Using two fuzzy clustering algorithms, the hyperspectral image can be clustered independent of the process of converting radiance values into the spectral reflectance. This can be done by comparing pixels to one another instead of comparing them to signatures in the spectra library.

In addition to clustering a hyperspectral image in an unsupervised manner, the proposed methods can solve the problem of identifying the objects for which the radiance of light makes it hard to identify them as a single object. This is done by making the values of a hyperspectral vector relative to one another and then applying any clustering algorithm.



(a) (b) (c) (d) (e) (f)

Fig. 5. (a) Result of applying FCM using Euclidean distance on hyperspectral data. (b) Result of applying FCM using Euclidean distance on derivative of hyperspectral data. (c) Result of applying FCM using cosine distance on hyperspectral data. (d) Result of applying FCM using cosine distance on derivative of hyperspectral data. (e) Result of applying fuzzy relational clustering on hyperspectral data. (f) Result of applying fuzzy relational clustering on derivative of hyperspectral data.

7. References

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