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Supervised Classification of Remote Sensing Images Using Fuzzy Technique

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Abstract

In the conventional remote sensing supervised classification, training information and classification results are represented in a one - pixel - one - class method. Class mixture cannot be taken into consideration in training classifier and in- determining pixels membership. The expressive limitation has reduced the classification accuracy level and led to the poor extraction of information. This paper describes a fuzzy supervised classification method in which geographical information is represented as fuzzy sets. The algorithm consists of two major steps: The estimate of fuzzy parameters from fuzzy training data, and fuzzy partitions of spectral space. Partial membership of pixels allows component cover classes of mixed pixels to be identified and more accurate statistical accuracy to be achieved. Results of classifying a landsat TM images are presented and their accuracy is analyzed.

الخلاصة

ان التصنيف الموجه لصور الاستشعار عن بعد باستخدام الطرق التقليديه تكون فيه بيانات الاستشعار عن بعد ونتائج التصنيف لهذه البيانات ممثله بحيث يكون كل عنصر في الصوره يمثل صنف واحد من اصناف الغطاء الارضي الموجود في الصوره. اما بالنسبه لاصناف الغطاء الارضي التي تكون متداخله او متشابكه فلا يمكن اخذها بنظر الاعتبار في عملية استخلاص البيانات الاختباريه او في عملية حساب درجة ارتباط كل عنصر من عناصر الصورة بذلك الصنف, ممايؤدي الى قلة دقة التصنيف و ضعف البيانات المستخلصة من الصورة.

في هذا البحث تم استخدام طريقة التصنيف المضبب لزيادة دقة التصنيف وجعل الاصناف المتداخله معرفه بشكل جيد. ان خوارزمية المحاميع المضببة المستخدمة في هذه الطريقه تتضمن مرحلتين : الاولى يتم فيها حساب معاملات التصنيف المضبب وفي المرحلة الثانيه يتم تقسيم الفضاء الطيفي للصورة الى محاميع وفق نظرية المجاميع المضببه. ان هذه الطريقه طبقت على صور مستحصله من القمر الصناعي لاند سات ذي متحسس نو ع (TM).

Introduction

The current remote sensing image analysis methods are unable to extract the majority of information dormant within digital remotely sensed data [1] and accuracy levels of images classification are quite often, unsatisfactory, that is because geographical information (including remote sensing derived information) is imprecise in nature .

This research reveals that an important factor which reduced the analysis quality lies in the loss of spectral information in the process of image classification. The information loss is caused by the current methods for representing geographical information [1]. In the current representation, a pixel can be assigned a single attribute with respect a given theme; e.g. cover class. Clearly, such a representation scheme has difficulty in dealing with situations which cannot be precisely described by a single attribute [2].

Fuzzy set theory [3] provides useful concepts and tools to deal with imprecise information. Partial membership allows that the information about more complex situations, such as cover mixture or intermediate conditions can be better represented and utilized. A fuzzy supervised classification method has been developed in this research; this method improves remote sensing image classification in the aspects of 1)- representation of geographical information, 2)- partitioning of spectral space, and 3)- the estimate of classification parameters.

Fuzzy Partition of Spectral Space

In remote sensing pixel measurement vectors are often considered as points in a spectral space. Pixels with similar spectral characteristics form groups which correspond to various ground – cover classes that the analyst defined.

The groups of pixels are referred to as spectral classes. To classify pixels into groups, the spectral space should be partitioned into regions, each of which corresponds to one of the information classes defined.

Traditionally, the information classes are implicitly represented as classical sets. Thus, a partition of spectral space is based on the principles of classical set theory. Such a partition is usually called a hard partition [1]. In a hard partition, as long as a pixel vector resides within spectral region, it is assigned a single cover class which corresponds to the spectral class. assignment implies full membership in that class and no membership in the other classes. The possibility that a pixel may partially belong to a class and simultaneously belong to more than one class is excluded. A great deal of valuable spectral information contained in pixel vector positions is discarded when the membership is determined. Final output of the classification is represented in a one pixel one class image. No information a bout the cover mixture or intermediate condition is available. This is an important reason for current poor extraction of spectral information.

Fuzzy set theory can provide a better representation for the geographical information, much of which cannot be described well by a single class. In a fuzzy representation for the geographical information, land cover classes can be defined as a fuzzy sets, and pixels as set elements. Each pixel is attached with a group of membership grades to indicate the extent to which the pixel belongs to certain classes.

Thus a spectral space is not partitioned by sharp surfaces and such partition is referred to as a fuzzy partition of spectral space [3]. Formally, fuzzy partition of spectral space is a family of fuzzy sets F_1, F_2 ....F_m on universe X such that Fuzzy set theory can provide a better representation for geographical information, much of which cannot be described well by a single class. In a fuzzy representation for geographical information, land cover classes can be defined as a fuzzy sets, and pixels as set elements. Each pixel is attached with a group of membership grades to indicate the extent to which the pixel belongs to certain classes. Thus a spectral space is not partitioned by sharp surfaces and such partition is referred to as a fuzzy partition of spectral space [3]. Formally, fuzzy partition of spectral space is a family of fuzzy sets F_1 ,F_2 ....F_m on universe X such that

$$\forall x \in X$$
$$0 \le fF_i(x) \le 1$$
$$\sum_{x \in X} fF_i\ (x) \ge 0$$
$$\sum_{i=1}^{m} fF(x) = 1 \qquad (1)$$

Where F_1,F_2,..F_m represents the spectral classes, X is the whole pixels, m is number of predefined classes, x is a pixel measurement vector, and fF_i is the membership function of the fuzzy set $F_i(1 \le i \le m)$.

The fuzzy partition can be recorded in a fuzzy partition matrix:

$$\begin{bmatrix} fF_1(x_1) fF_1(x_2) .... fF_1(x_n) \\ fF_2(x_1) fF_2(x_2) .... fF_2(x_n) \\ .... \\ fF_m(x_1) fF_m(x_2) .... fF_m(x_n) \end{bmatrix} \qquad (2)$$

Where n is the number of pixels, and x_i's are pixels ($1 \le i \le n$). A hard partition matrix can be derived from the fuzzy partition matrix by changing the maximum value in each column into "1" and others into "0".

A fuzzy partition of spectral space can represent a real situation better than a hard partition and allows more spectral information to be utilized in subsequent analysis. Membership grades can be used to describe cover class mixture and intermediate cases, another advantage of the fuzzy partition in cluster analysis is that stray pixels and pixels isolated between classes may be classified as such[4],[5].

Fuzzy Parameters for Image Classification

In this study a simple idea is used to modify the traditional maximum likelihood method by introducing the notions of fuzzy means and fuzzy covariance matrices beforehand calculated [3].
For each class, a representative fuzzy signature which takes into account the actual class composition for each pixel in the signature is chosen. Hence, from the obtained set of "class extent signatures", the following parameters are deduced for each class C:

1-The fuzzy means:

$$\mu_c = \frac{\sum_{i=1}^{n} f_c(x_i).x_i}{\sum_{i=1}^{n} f_c(x_i)} \qquad (3)$$

Where μ_c is Fuzzy mean of class (**c**), $f_c(x_i)$ is the membership function of class c, x_i is a simple pixel measurement vector, and n is the total number of sample pixel measurement vectors.

2- The fuzzy covariance matrices:

$$\text{cov}_c = \frac{\sum_{i=1}^{n} f_c(x_i)(x_i-\mu_c)(x_i-\mu_c)^T}{\sum_{i=1}^{n} f_c(x_i)} \qquad (4)$$

Where cov_c is the fuzzy covariance matrix element of class **c**.
Then, the fuzzy membership degrees are computed by applying the maximum likelihood procedure using the above fuzzy parameters of the signature (fuzzy means and fuzzy covariance matrices).
From viewpoint of mathematics, the extent of the class **c** in a multidimensional pixel **x** is:

$$f_c(x) = \frac{p_c(x)}{\sum_{i=1}^{c} p_i(x)} \qquad (5)$$

Where **c** is the number of information classes and:

$$p_i(x) = \frac{1}{(2\pi)^{N/2}|\text{cov}_i|}\exp\left[-\frac{1}{2}(x-\mu_i)^T \text{cov}_i^{-1}(x-\mu_i)\right] \qquad (6)$$

Where: N is the dimension of the pixel vectors.

Results and Discussion

The results have been obtained in applying the fuzzy supervised classification algorithm to landsat (TM) images. In this algorithm the whole area was classified by using ground information from selected areas (training areas), this training areas contains (36) vectors of each category or class, and these classes are (Water, Forest, Grass, Bare, Urban) [6]. The study area associated with this project centers on the upper Mississippi River basin as shown in fig (1).

Fig (1): An Aerial Photograph of the Mississippi River Basin

Table (1) represents the confusion matrix of the conventional maximum likelihood classification. It can be concluded from the confusion matrix that the overall accuracy of this method is 88 percent.
Improvement in overall classification accuracy has been achieved using the fuzzy mean and fuzzy covariance matrix. The statistical parameters generated by the fuzzy and conventional algorithms are somewhat different.

Table (2) shows the conventional and fuzzy means of five classes.

Note:

W=water
F=forest
G=grass
B=bare
U=urban

Table(1): Confusion Matrix

	W	F	G	B	U	%
W	33	2	1	0	0	91
F	2	31	3	0	0	86
G	1	4	30	1	0	83
B	0	0	1	33	2	91
U	0	0	0	3	33	91

Overall Accuracy = 88%

Table (2): Fuzzy and conventional Means

Band		3	4	6
W	Fuzzy	32.1	29.4	24.1
	Conv	32	29.5	23.7
F	Fuzzy	37	36.9	108.2
	Conv	35.7	34.8	108.7
G	Fuzzy	43.1	47.5	104.5
	Conv	43	47.3	104.7
B	Fuzzy	57.8	72.2	103.5
	conv	61.2	78.2	106.5
U	Fuzzy	51.3	60.8	67.8
	conv	51.1	60.5	67

And the following are the fuzzy and conventional covariance matrices for the class of Urban areas:

Fuzzy covariance matrix =

$$\begin{bmatrix} 57.05 & 78.18 & 78.89 & 76.13 \\ 78.18 & 120.22 & 109.47 & 101.67 \\ 78.89 & 109.97 & 210.24 & 246.91 \\ 76.13 & 101.67 & 246.91 & 317.11 \end{bmatrix}$$

Conventional covariance matrix =

$$\begin{bmatrix} 58.50 & 80.60 & 83.32 & 81.36 \\ 80.60 & 123.99 & 117.82 & 111.28 \\ 83.32 & 117.82 & 211.72 & 244.83 \\ 81.36 & 111.28 & 244.38 & 308.81 \end{bmatrix}$$

Fig (2) is the classification image of the study area and table (3) is the confusion matrix of the fuzzy maximum likelihood classification.

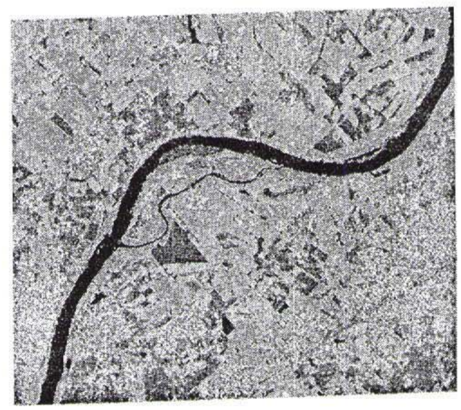

Fig (2): Classification Output of the Fuzzy Method

Table (3): Confusion Matrix of the Fuzzy Classification

	W	F	G	B	U	%
W	35	1	0	0	0	97
F	0	35	1	0	0	97
G	0	2	34	0	0	94
B	0	0	1	35	0	97
U	0	0	4	2	30	83

Overall accuracy = 93

It can be concluded from this confusion matrix that the overall accuracy of fuzzy classification results 93.88 percent and an improvement of (5) percent has been achieved.

Conclusion

In this study, a new method for fuzzy supervised classification has been proposed.
which is well-suited with the nature of the information to be processed. However this point is not always given deserved attention in developing new processing techniques and improving the processing quality and efficiency. On the contrary, improvement in representation might achieve twice the benefit with half the effort.

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