Improved Classification Algorithm using Extended Fuzzy Clustering and Maximum Likelihood Method

Young-Joon Jeon and Jin-Il Kim
Department of Computer Engineering, Dongeui University
San 24, Kaya-Dong, Busanjin-Ku, Busan, Korea
Tel. +82-51-890-1705, Fax. +82-51-890-1704
e-mail : j4017@chol.com, jlkim@deu.ac.kr

Abstract:
This paper proposes remotely sensed image classification method by fuzzy c-means clustering algorithm using average intra-cluster distance. The average intra-cluster distance acquires an average of the vector set belong to each cluster and proportionates to its size and density. We perform classification according to pixel's membership grade by cluster center of fuzzy c-means clustering using the mean-values of training data about each class. Fuzzy c-means algorithm considered membership degree for inter-cluster of each class. And then, we validate degree of overlap between clusters. A pixel which has a high degree of overlap applies to the maximum likelihood classification method. Finally, we decide category by comparing with fuzzy membership degree and likelihood rate. The proposed method is applied to IKONOS remote sensing satellite image for the verifying test.

1. INTRODUCTION

Remote sensing is the science of gaining information about the earth's surface by analyzing date acquired from a distance. Since the first resource satellite was launched in 1972, the remote sensing community has witnessed impressive progress in remotely sensed imagery, in both quality and quantity. The greatest progress has been in the improvement of the spectral and spatial resolutions. High spectral-resolution images have hundreds of bands to monitor the earth's surface down to the molecular level. High spatial-resolution images can be used essentially in a manner similar to large-scale aerial photos. Up to the present, various methods have been developed for extracting land use/cover information from remote sensing data by performing multi-spectral classification on the electromagnetic spectrum of geometric registered remote sensing data [1][2].

In general, a classification of a remotely sensed image can be seen as an iterative process in which each of its pixels in assigned to one of the several predefined land cover classes to be mapped. The computer uses decision boundaries to divide pixels into information groups based on their spectral reflectance values. Parametric techniques use statistical approaches to determine how to classify unknown pixels, while non-parametric techniques rely on non-statistical methods such as geometry-based approaches. The procedure used for classification depends on whether there is a prior information about the image[3]. There are two main types of classification procedures: supervised and unsupervised. The supervised approach relies on a prior ground truth data. Training areas are selected from the image such that pixels within that geographic area are representative of the spectral response pattern of a particular information class. For the classification to be accurate, the training data for each information class must capture the variability within objects in the class. When a classification is run, the computer uses the training data to form decision boundaries, and then assigns unknown pixels into information classes based on these established boundaries. Unsupervised techniques are utilized when no a prior information about image is available. The computer searches the data in feature space for natural clusters of pixels with similar spectral response patterns. Rather than providing training data for information classes before classification, the analyst must interpret the spectral classes that result from the classification and assign them to the appropriate land cover class. A study of satellite image classification methods examines the Parallelepiped, Minimum distance, Maximum likelihood, Fuzzy supervised classification methods, as well as the unsupervised methods of the Sequential clustering, K-Means clustering, ISODATA, and Fuzzy C-Means clustering classification methods[3]4].

This paper shows high resolution satellite image classification method integrated by maximum likelihood classification(MLC) and fuzzy clustering used to average intra-cluster distance. The results shows that proposed method could improve performance of classification method.

2. PROPOSED CLASSIFICATION METHOD

This paper studied remotely sensed image classification method by fuzzy c-means clustering algorithm using average intra-cluster distance. Fig 1 shows a schematic diagram for proposed classification procedure. The selection of appropriate training areas is based on the analyst's familiarity with the geographical area and their knowledge of the actual surface cover types present in the image. By next time, we can perform classification according to pixel's membership grade followed by cluster center of fuzzy c-mean clustering as the mean value of training data. Fuzzy c-means clustering algorithm considered membership degree for inter-cluster of each pattern. Next procedure calculates degree of overlap between clusters. A pixel which has a high degree of overlap applies to the maximum likelihood classification method. Finally, we decide category by comparing with fuzzy membership degree and likelihood rate.

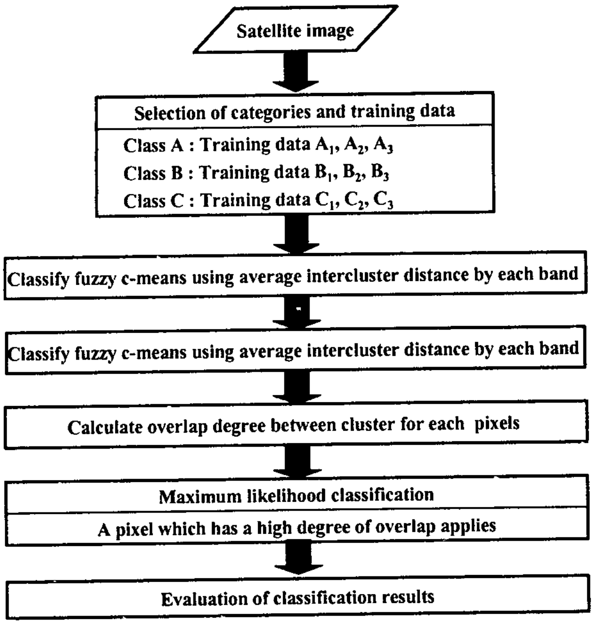

Fig 1. Schematic diagram for proposed classification procedure

2.1 Fuzzy c-means algorithm

The Fuzzy C-Means clustering method creates a membership grade to belong to the cluster using a fuzzy coefficient and it allocates pixels to the cluster. The Fuzzy C-Means (FCM) algorithm is a constrained optimization problem which minimizes the following objective function with respect to membership functions μ_{ij} and cluster centroid v_i,

$$J_m(U,V;X)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}{}^{m}\left\|x_j-v_i\right\|^2$$

where $V=(v_1,\cdots,v_c)$ is a vector of cluster centers $U=[\mu_{ij}]$ is a $c\times n$ matrix, c is the number of clusters, n is the number of data points, satisfying the conditions as

$$M_{fcn}=\left\{U\in R^{cn}\,\middle|\,\mu_{ij}\in[0,1]\,\forall i,j;\ 0<\sum_{j=1}^{n}\mu_{ij}<n\ \forall i,\ and\sum_{i=1}^{c}\mu_{ij}=1\,\forall j\right\}$$

$V=(v_1,\cdots,v_c)$ is a vector of cluster centers, $v_i\in R^p$ for $c\geq i\geq 1$ and $\|\bullet\|$ denotes any inner product norm.

The parameter $m\in[1,\infty)$ is a weighting exponent on each fuzzy membership. Minimization of the above objective function, J_m requires the membership values to be defined as

$$u_{ij}=\left[\sum_{k=1}^{c}\left(\frac{D_{ijA}}{D_{jkA}}\right)^{\frac{2}{m-1}}\right]^{-1},\quad 1\leq i\leq c;\ 1\leq j\leq n$$

and the class centers as

$$v_i=\frac{\sum_{j=1}^{c}\mu_{ij}{}^{m}x_j}{\sum_{j=1}^{n}\mu_{ij}{}^{m}},\quad 1\leq i\leq c.$$

where

$$D_{ij}=\left\|x_j-v_i\right\|_A>0\ \ \forall i,j,$$

D_{ij} is distance between the feature vector X_i and the cluster center v_i. Each class represents one of the given spectral signatures in the prototype library. This paper use training data from the images to define the class centers (v_i^0), and then the pixels are classified by calculating the membership degree μ_{ij}.

2.2 Extended fuzzy clustering algorithm

Most of fuzzy clustering methods have used the Fuzzy C-means (FCM) algorithm. This algorithm can be misclassified about the different size of cluster because the degree of membership depends on highly the distance between data and the centroids of the clusters. Therefore, this paper fuzzy c-means algorithm considered membership degree for average intra-cluster distance of each class. The average intra-cluster distance take an average of the vector set belong to each cluster and increase in exact proportion to it's size and density.

The objective function which satisfies our requirements may be formulated as

$$J_m(U,V;X)=\sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ij}{}^{m}\left\|x_j-v_i\right\|^2-\sum_{i=1}^{c}\eta_i\sum_{j=1}^{n}(\mu_{ij})^m$$

$$\sum_{i=1}^{c}\mu_{ij}=1\ \text{ for all } j$$

Where η_i are suitable positive numbers. The first term demands that the distance from the feature vectors to the prototypes be as low as possible.

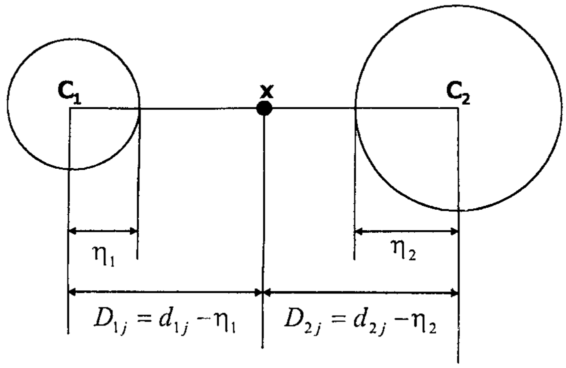

Fig 2. Distance between the feature vector and the cluster center.

D_{ij} denotes distance from jth pixel to ith intra cluster. If D_{ij} <0, pixels belong on intra cluster. Fig 2 shows distance between the feature vector X_i and the cluster center v_i at extended fuzzy clustering algorithm.

η_i is used to formula that is defined by Krishnapuram[5][6].

$$\eta_i = K \frac{\sum_{j=1}^{n} \mu_{ij}^m d_{ij}^2}{\sum_{j=1}^{n} \mu_{ij}^m}.$$

This choice makes η_i proportional to the average intra-cluster distance of cluster. Typically K is chosen to be 1.

2.3 Maximum likelihood classification

After perform fuzzy c-means clustering algorithm, we decides degree of overlap between clusters. The overlap measure is obtained by computing an inter-cluster overlap. A better result from fuzzy clustering classifications is expected to have a low degree of overlap.

This paper computes the degree of overlap as following:

1) Perform fuzzy c-means algorithm by each band.

2) Decide membership degree of pixel belong to each class by band.

3) if $\mu \le \mu_{C_1}(x_j)$, $\mu \le \mu_{C_2}(x_j)$ is overlaped pixel.

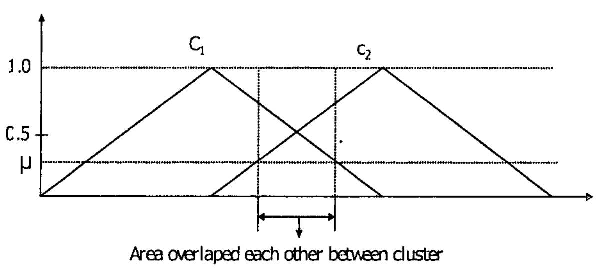

Fig 3. Overlap value between clusters

Fig 3 shows overlap value between clusters. A pixel which has a high degree of overlap applies to the maximum likelihood classification method. The maximum likelihood decision rule is based on the probability that a pixel will belong to a particular class. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions. That is, it calculates the pixel data's likelihood to fall into each class and the algorithm assigns the pixel to the class with the maximum likelihood[7]. The equation for the maximum likelihood classifier is as follows:

$$P(X \mid w_i) = \frac{1}{(2\pi)^{N/2} \left|\sum_i\right|^{1/2}} \exp\left[-\frac{1}{2}(X - U_i)^T \sum_i^{-1} (X - U_i) \right]$$

X : the measurement vector of the candidate pixel
U_c : the mean vector of the each class
Σ_c : the covariance matrix of the pixels in the class i
Σ_c^{-1} : inverse of $_c$
T : transposition function(matrix algebra)
$|_c|$: determinant of Σ_c (matrix algebra)

Finally, we decide category by comparing with fuzzy membership degree and likelihood rate.

3. EXPERIMENTS AND RESULTS

We simulated a set IKONOS satellite imagery having spatial resolution of 1m×1m. The image size used for the experiment is 1000×1000 pixels and it is consisted of 4 band. We selected each training data for 6 classification items and executed classification. We conformed whether the training data are classified exactly for chosen item. As a result of the experiment using IKONOS satellite image, it shows that proposed method could improve performance of classification rather than the conventional maximum likelihood classification method. Table 1 shows classification correctness about training data.

Table 1. Classification results

Classification item		Forest	Water	Urban	Ground	shadow
Number of training pixels		4824	12258	6420	19148	2341
Classification method	Maximum likelihood	88%	87%	93.5%	91.4%	86.5%
	Proposed method	96%	98%	95%	96%	95%

We also could confirm applicability for classification accuracy improvement of high resolution satellite imagery. Fig 4 shows the classification results of proposed method.

Fig 4. The classification results of proposed classification method.

4. CONCLUSIONS

This paper proposes remotely sensed image classification method by fuzzy c-means clustering algorithm using average intra-cluster distance. We can classify according to pixel's membership grade by cluster center of fuzzy c-means clustering using the mean value of training data. Fuzzy c-means clustering algorithm considered membership degree for inter-cluster of each pattern. As next process, we validate degree of overlap between clusters. A pixel which has a high degree of overlap applies to the maximum likelihood classification method. Finally, we decide category by comparing with fuzzy membership degree and likelihood rate. As a result of the experiment using IKONOS satellite image, it shows that proposed method could improve performance of classification rather than the conventional maximum likelihood classification method. We also could confirm applicability for classification accuracy improvement of high resolution satellite image.

In the future, we will achieve a research for selection method of correct training data and solution of pixel classification for shadow portions.

References

[1] John A. Richards, *Remote Sensing Digital Image Analysis : An Introduction*, Second, Revised and Enlarged Edition, pp. 229-262, Springer-Verlag, 1994.

[2] J. M. Cloutis, " Hyperspectral geological remote sensing: Evaluation of analytical techniques," International Journal of Remote Sensing, 17(12), pp. 2215~2242, 1996.

[3] David Landgrebe, *Information Extraction Principles and Methods for Multispectral and Hyperspectral Image Data*, Chapter 1 of Information Processing for Remote Sensing, edited by C. H. Chen, published by the World Scientific Publishing Co., Inc., pp. 1-30, Spring, 1999.

[4] N.R. Pal and J.C. Bezdek, "On cluster validity for the fuzzy c-means model", IEEE Transactions on Fuzzy Systems, Vol. 3, No. 3, pp.370 379, 1995.

[5] R. Krishnapuram, H. Frigui and O. Nasraoui, "Fuzzy and Possibilistic shell Clustering algorithms and their application to boundary detection and surface approximation," IEEE Trans. on Fuzzy Systems, Vol. 3, No. 1, pp. 29-60. 1995.

[6] R. Krishnapuram and J. M. Keller, "A possibilistic approach to clustering," IEEE Trans. on Fuzzy Systems, Vol. 1, No. 2, pp. 98-110, 1993.

[7] B.Gorte and A. Stein. "Bayesian classification and class area estimation of satellite images using stratification," IEEE Trans. On Geoscience and Remote Sensing, 36(3):303, 1998.