IMAGE SEGMENTATION IN UNSUPERVISED AND SUPERVISED LAND COVER CLASSIFICATION FROM SATELLITE IMAGES

EIJA PARMES
Research Scientist

RISTO KUITTINEN
Senior Research Scientist

TECHNICAL RESEARCH CENTER OF FINLAND
ESPOO, FINLAND

Commission III, WG 4

ABSTRACT

The paper describes an interpretation method for land cover from satellite images based on the segmentation of the image area and unsupervised nonparametric frequency table clustering. The image area is segmented into homogeneous units. The segmentation result is used in the clustering to increase the class separability by eliminating the mixed and boundary pixel values from the observations to be clustered. Both the segmentation and the clustering are based on merging algorithm towards lowest/highest gradient intensity.

To test the distributions of the classes from this segmentation based non-parametric unsupervised method for delineation of land cover classes from satellite images, a Spot-satellite image were classified based on the classes from this clustering method with three different classifiers, which suppose different forms from the distributions. The nonparametric classifier used directly the clustered frequency table for look-up table classification. The linear discriminant function for minimum error and the maximum likelihood method used as training areas the classification result from this nonparametric classifier. The small differences in the accuracies prove the validity of the unsupervised frequency table clustering, which is based only on the distribution of the frequencies of the feature vectors, without any assumption on the density functions of the classes.

These classification results were further processed so that the mode class was assigned to each segment. The effect of the mode class assigment to the segments improved in most cases the accuracy by 1-4 %. It gives a more appropriate end product for use.

1. INTRODUCTION

The numerical interpretation methods of satellite images can be divided into supervised and unsupervised methods and both further into parametric and non-parametric methods.

The supervised determination of classes is done by the feature vectors of user selected training areas. The delineation of the training areas for one 1 : 50 000 map area takes 2-4 working days. In parametric methods the classes are usually supposed to have a multinormal density and the classification of pixels is done by a distance or probability measure from the density function parameters (for instance maximum likelihood method and linear discriminant function methods minimizing classification error). These methods are largely used in the interpretation of satellite imagery. Also based on training areas for instance the relations between forest variables and radiometric values has been modelled (/Tom 87/). In nonparametric methods the classes are defined by the frequency tables of each class calculated from the training areas (for instance Parzen classification method).

In unsupervised methods the feature vector space is clustered into classes without training information. In parametric methods a more or less systematic class mean group is generated for iteration. The feature vectors are classified to their nearest classes, new class means and covariances are calculated, classes are divided or grouped by user given maximum standard deviation and minimum distance measures. These steps are repeated until stability is reached.

In unsupervised non-parametric classification methods the frequency table of the feature vectors is divided into distinct clusters. This type of classification method was choosed for development the objectives being objectivity and minimal man interaction. The unsupervised nonparametric classification is sensitive to the separability of the classes. This was increased by the elimination of mixed and boundary pixels from the feature space to be clustered. The mixed and boundary pixels are defined by the initial segmentation of the satellite image.

The segmentation and the frequency table clustering are both based on the directed trees algorithm presented in /Nar 77/ and /Nar 80/. The algorithm of the frequency table clustering is treated also in /Wha 83/ and /Rou 87/.

2. THE UNSUPERVISED NON-PARAMETRIC CLASSIFICATION METHOD

2.1 General

The segmentation based unsupervised nonparametric classification method was developed in the Technical Research Center of Finland with financing from the National Board of Survey and the Topographic Service of the Finnish Defense Forces. The classification method has been included to the Disimp program package, originating from Csiro, Australia. It is coded in Fortran and running in VAX 11/750 of the Technical Research Center.

The method includes the segmentation of the original satellite image into homogeneous units, the choosing of representative values of the segments for frequency table clustering, the classification of the image table by the resulting clustered frequency table and finally the assignment of each segment's mode class to the segment as a generalization phase. The classification is unsupervised with the exception of two thresholds, one affecting to the resulting number of segments and the other to the resulting number of classes.

2.2 Segmentation

The segmentation method is based on the linking of pixels to the neighbouring pixel with minimum gradient intensity. The method needs one threshold e, which prevents the linking towards a too great relative gradient. The increase of the threshold decreases the number of boundaries without affecting to the exact location of the remaining boundaries. The pixels linked together are assigned to the same segment. The method produces closed boundaries. It is not sensitive to the absolut difference of radiometric values on boundaries. The pixels are processed in the following four steps :

1. Calculation of maximum gradient intensity sum (maximum over directions and sum over channels)

$$G(x,y) = \sum_{n=1}^{nch} (\max_{k=1,nk} | \sum_{i=-1}^{1} \sum_{j=-1}^{1} M_k(i,j) * I_n(x+i, y+j)|)$$

where I = image matrice, nch=number of channels and nk=number of boundary templates M. The boundary templates $M(3x3)$ correspond to the directions 0/360, 45/315,90/270 and 135/225 degrees.

2. Calculation of the maximum difference between the pixel and its neighbouring pixels and the determination of evident root pixels and boundary pixels.

$$D(x,y) = \max_{i,j=-1,1} (G(x,y) - G(x+i, y+j))$$

- if $D(x,y) < -e$: evident root pixel, no linking

- if $D(x,y) > e$: evident boundary pixel, linking to the neighbouring pixel with minimum gradient.

3. The linking of remaining pixels to the neighbouring pixels with minimum gradient and without producing cycles.

4. Tracing of the resulting trees and assignment of labels to the segments.

2.3 Feature extraction and clustering

The pixels representing the segments in the clustering are those with minimum local variation inside the segment. The frequency table is calculated from the observations of these pixels.

The clustering of the frequency table F is based on the same directed trees algorithm described in 2.2 The frequency values are linked to the neighbour value with maximum frequency. The algorith needs one threshold e, which affects to the number of the resulting clusters or classes. The decrease of the threshold increases the number of classes without affecting to the location of the class boundaries resulting with greater threshold.

1. The calculation of the maximum difference between a frequency value and its neighbouring values and the determination of evident values and class boundary values.

$$D(x,y) = \max_{i,j=-1,1} (F(x,y) - F(x+i, y+j))$$

- if $D(x,y) > e$: evident local maximal frequency, no linking

- if $D(x,y) < -e$: evident class boundary value, linking to the neighbour with maximum frequency value.

2. Linking of the remaining frequency values to the neighbour with maximum frequency without resulting cycles.

3. Tracing of the resulting trees and assignment of individual labels to the trees, or classes.

The algorithm is not sensitive to the absolute radiometrical values, because the classes are determined as clusters in the frequency table. It produces directly a look-up table for the classification of image pixels.

2.4 Assignment of classes to the segments

The individual image pixels are assigned to the proper classes by the look-up table from the clustering. As a generalization phase, the segments are the assigned to their mode class : this eliminates, especially from the boundaries, separate pixels. The segment classification produces also for each segment a measure of homogeneity, ie. the proportion of the mode class pixels to the total number of pixels in that segment. This measure can be used for the determination of bad segments.

3. THE PROCEDURES FOR THE CLASSIFICATIONS

A Spot-image of Lohja test area with a surface of $10x20km^2$ in Southern Finland was interpreted by the unsupervised frequency table clustering. The segmentation used observations from the three channels and the clustering from red and infrared channels. The frequency table was calculated from the reference pixels of the segments, ie. only one pixel per segment was included in the clustering.

The segmentation resulted into 17 216 segments with a threshold 13. The clustering of the segments' reference pixels' observations resulted to 37 radiometrical classes with the threshold 15. From these 3 were assigned to water areas (clear water, sediment including water and vegetated water), 3 to coniferous forest, 2 to other forest land ja 4 to cultivated land. 14 classes were left unclassified, their proportion of the map area was 3 %.

The classified areas from the unsupervised method were used as training areas for the supervised classifications. The mean M and covariance matrices C were calculated from these training areas.

The used linear discriminant functions $H(X) = V^t(X) + v_o$ for minimum error /Fuk 72/ minimize the theoretical classification error of normal distributions with unequal covariance matrices.

However, it does not imply multinormality from the distributions. The discriminant function coefficients V and v_o are determined by an iterative process and $H(X)$ is determined for each class pair with mean and covariance vectors M_1, M_2, C_1 and C_2.

$$V = [sC_1 + (1-s)C_2]^{-1}(M_2 - M_1)$$

$$\sigma_i = V^T C_i V$$

$$v_o = \frac{-[s\sigma_1^2 V^T M_2 + (1-s)\sigma_2^2 V^T M_1]}{s\sigma_1^2 + (1-s)\sigma_2^2}$$

The coefficients V and v_o were calculated with values s ranging from 0 to 1 with 0.1 increments. The values minimizing the theoretical error between two normal distributions are choosed.

The maximum likelihood classification implies multinormality from the class distributions. The decision function between two classes is :

$$h(X) = (X - M_1)^T C_1^{-1}(X - M_1) - (X - M_2)^T C_2^{-1}(X - M_2) + ln\,\frac{|C_1|}{|C_2|} - 2\,ln\,\frac{P_1}{P_2}$$

where X is the vector to be classified and P_i the a priori probability of class i. The mean and covariance matrices M_i and C_i were calculated from the classified areas of the nonparametric unsupervised classification method.

4. RESULTS

4.1 Image geometry

The Spot satellite multispectral image of Lohja test area with a surface of $20x30km^2$ were rectified to map coordinate system by nearest neighbour interpolation and a polynomial first degree transformation based on 10-15 control points measured from 1: 50 000 map. The interpretation results of Lohja test area were compared to the digitized water element of the 1 : 50 000 topographic map. The measurement of 45 lake boundary points resulted to maximum differences of 44 m in easting and 46 m in northing, and to root mean squared errors of 19 m in easting and 21 m in northing. These differences are included in the comparison of the classification results to the digitized map elements.

4.2 Classification results

The classification results were compared pixel by pixel to the digitized water and cultivated land elements of the official map 1 : 50 000. Table 1 shows the confusion table. The values include the effect of geometrical differences between the map and the rectified satellite image.

TABLE 1 : Classification accuracies for water and cultivated areas with different methods. Pixel by pixel classification. Nonp: nonparametric look-up table classification, lind: linear discriminant function classifier and mxlk: maximum likelihood classifier. Comparison pixel by pixel to digitized map elements. The omission is the percentage to the map area and commission the percentage to the interpreted area.

	map area (ha)	int. area (ha)	omission (%)	commission (%)
water nonp	119	114	8	3
water lind	119	120	6	6
water mxlk	119	117	6	4
cultiv nonp	353	394	14	23
cultiv lind	353	385	14	21
cultiv mxlk	353	389	14	22

Each classification result was further processed so that the segments of the segmentation result were assigned to their mode class. This eliminated separate pixels especially from the boundaries of the segments. The results from the comparison to the map elements are shown in Table 2.

TABLE 2 : Classification accuracies for water and cultivated areas with different methods. Pixels are assigned to the mode class of their segment. Nonp: nonparametric look-up table classification, lind: linear discriminant function classifier and mxlk: maximum likelihood classifier. Comparison pixel by pixel to digitized map elements.

	map area (ha)	int. area (ha)	omission (%)	commission (%)
water nonp	119	119	5	4
water lind	119	121	5	5
water mxlk	119	120	5	5
cultiv nonp	353	409	10	22
cultiv lind	353	394	11	21
cultiv mxlk	353	390	13	21

To evaluate the effect of geometrical differences the confusion matrice was calculated by shifting the interpretation result one pixel to 8 directions. The shifts giving optimal results were different in the different parts of the map : the greatest differences in the surface of the cultivated area were 4 %.

5. CONCLUSIONS

To test the validity and the class distributions of a segmentation based nonparametric unsupervised frequency table classification of a Spot image, the image was classified for comparison with 2 supervised classifiers.

The supervised classifiers used the training statistics originating from the classification results of the frequency table clustering. So the comparison does not directly test the classification accuracies resulting from the different classifiers : this is largely affected by the user chosen training areas. Instead, it testes the distributions of the classes resulting from the nonsupervised frequency table clustering, where the classes are defined only by the distribution of the frequencies of the feature vectors, without any assumptions on the density functions of the classes.

The small differences in the classification errors between the classifiers prove the validity of the unsupervised frequency table clustering method. The classification errors with different classifiers are greater than the differences in classification errors.

These classification results were further processed so that the mode class was assigned to each segment of the segmented Spot image. The effect of the mode class assigment to the segments improved in most cases the accuracy by 1-4 %. It gives a more appropriate end product for use.

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