

GEOCLASS, A NEW APPROACH TO THE THEMATIC CLASSIFICATION OF MULTISPECTRAL IMAGERY

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ABSTRACT :

The use of digital multispectral imagery for thematic classification has become standard practice. In a conventional approach only color attributes of individual pixels are used in classifying terrestrial objects. Since many terrestrial features possess similar color attributes, thematic classifications solely based on color attributes are often inaccurate. A new approach has been implemented that in addition to color takes also into account the spatial relationship of individual pixels to their neighbours. The use of spatially related information greatly enhances the analyst's ability to make improvements to the type of thematic classes that can be extracted and to their accuracy. This was demonstrated by a successful application of this approach to the classification of crop types using TM imagery.

KEY WORDS: Algorithm, Image Segmentation, Image Analysis, Image Interpretation.

1. INTRODUCTION

Although twenty years have passed since the first Earth Resources Satellite (Landsat 1) was launched, the utilisation of imagery data provided by this type of satellite for thematic mapping has not yet fulfilled the early expectations raised by this new type of environmental data (Ryerson, 1989). While the quality of the data both in terms of spatial and spectral resolution has improved during this time span (e.g. TM vs. MSS), the same cannot be said for the computer-based methodologies applied to the extraction of thematic information from the physical data. In particular, the approaches and techniques used in these methodologies have not progressed substantially since that time. The conventional approach assumes that individual picture elements (pixels) represent actual classification objects by ignoring any other pixel attribute but color. As pointed out by Sijmons (1987): "treating scene elements as independent objects is an incorrect model that ignores structural features which explicitly consider the spatial relationship between neighbouring elements". If the spatial element is not taken into consideration, "mixture" pixels, those pixels where two or more terrain cover types mix, cannot be distinguished from "pure" pixels that represent a single land cover type. In addition, many land features characterized by a typical spatial configuration, such as roads, cannot be distinguished. Usually, roads generate spectral signatures very similar to all other man-made objects found in built-up areas. Clearly, the discriminating algorithm to be applied in any attempt to identify the linear pattern of roads will have to take into consideration both the spectral and spatial attributes of pixels. The addition of the spatial configuration of pixels to multispectral color in the analysis of remotely sensed imagery data is not only useful for classifying specific thematic categories, such as roads, but should be considered an essential element for improving the accuracy of any type of thematic classification. In fact, using spatial attributes it is indeed possible not to be any longer bound by the erroneous concept of representing pixels

as classification objects. Through a segmentation process a terrestrial scene can be partitioned into areal and linear structural elements, characterized by the association of pixels having similar spectral and spatial properties. These structural elements will have a much closer link to land features than individual pixels, bringing about significant improvements to the entire process of image classification. This paper describes the design and development of GEOCLASS, the first computer-based methodology commercially available capable of analysing multispectral imagery in both the spectral and spatial domain.

2. CONVENTIONAL APPROACH

To illustrate the advantages to be gained by the GEOCLASS methodology, a short review of the shortcomings of the conventional approach based on pixel processing is required. The basic premise in computer-assisted multispectral classification of remotely sensed imagery is that terrestrial objects display sufficiently different reflectance properties in different regions of the spectrum to allow specific colors to be associated to specific objects. This is in general a valid assumption. However, this assumption should not be meant to imply that every picture element of two different objects is different in color. For instance, if it is true that the average color of a wheat field in a satellite summer image is different from that of a field of canola, it is not true that every pixel belonging to a wheat field is necessarily different in color from every pixel belonging to a field of canola. Ignoring this fact leads to a number of problems that permeate throughout the entire conventional classification process. However, there is even a more serious drawback. This has to do with the most important aspect of image classification, which is the choice of training samples. Training is the initial stage of the pattern recognition process followed in remote sensing. It consists of determining a valid sample for the spectral signatures of all objects existing within a selected scene. A valid sample means that the sample must best represent an entire population of a specific land feature. Since all classifiers commonly used in remote sensing rely on

the measure of distances of pixels from class centres, the sample that best represent a specific land feature is the one which best define the centre of such class. In conventional methodologies samples are either a) arbitrarily selected by visual inspection of a video display of imagery data (supervised classification) or b) automatically selected by implementing some form of clustering technique on raw data (unsupervised classification). Both of these techniques could possibly work only if color distinctions between populations of terrestrial objects would be sharp and no color overlap would exist between neighbouring classes, which is certainly not the case in remote sensing. In fact, in the majority of cases only a few radiance levels separate a class from the next. Even a skillful image analyst would find very difficult, if not impossible, to outline visually on a video screen samples that will define the actual location of class centres, so that valid statistical discriminating functions can be applied. Moreover, if variance values are also computed from these samples, as normally done with the maximum likelihood decision rule, the wrong assumption is also made that the sample variance, which in the majority of cases depends mostly on local factors (e.g. the presence of discontinuities in the canopy of crops), does somehow reflect the actual variance of an entire class of objects. As to the application of clustering techniques, the presence of "mixture" pixels together with the color overlap existing among various classes makes it very difficult to find valid histogram peaks, i.e. peaks that do represent class centres.

3. GEOCLASS APPROACH

3.1 Image Segmentation

Let us look now at the solutions to these problems provided by the GEOCLASS approach. First of all, it was found necessary to isolate object populations from each other through a segmentation process based on the extraction of boundaries that delimit regions of homogeneous color. This process is done in stages and is illustrated by Figure 1. The upper left quadrant depicts a 4.5x3.5 kms agricultural test site located in Manitoba, Canada. This site was used for an in-depth evaluation of the capabilities of the TM sensor to discriminate a variety of field crops: potatoes, flax, cereals, peas, rapeseed (canola), etc. (Steffensen and Mack, 1986). This enhanced portion of a TM scene gathered on July 1, 1984 was produced using band 4: red, band 7: green, band 2: blue. Fallow and potatoes appear as green tones, cereals as red tones, peas and canola as pink tones, woodlands as dark red tones. The upper right quadrant shows the results of extracting gradient values for each pixel. This is done by measuring a non-directional gradient value occurring within a 3x3 cell centered on each pixel. This process is applied band by band. If a pixel is surrounded by pixels of the same value in a specific band it will have a zero gradient value in that particular band. The higher the difference between the center pixel and its eight neighbours, the stronger the gradient value. The end result of this automated computation is a subimage in which dark areas are areas of color homogeneity and bright lines mark the color changes occurring within the scene. It can be seen on figure 1 that high gradient values affect a few pixels at the edge of each agricultural field and that different gradient values occur in different bands, depending on the crop types involved. Yellow lines (high gradient values in bands 4 and 7) mark the boundaries between exposed soil and vegetation, while purple lines (high gradient values in bands 4 and 2) mark boundaries between different green crops. To further understand how the upper right quadrant of figure 1 is related to the upper left quadrant, one can

focus his attention on the triangular feature appearing on the upper left quadrant. This is an abandoned airport. Since the runways are represented by more than one pixel in width the gradient algorithm is capable of isolating a black low-gradient pixel having on both sides bright high-gradient pixels (see right side). Now, by applying a ridge-edge extraction algorithm to the upper right quadrant we obtain the subimage illustrated in the lower left quadrant, where precise boundary lines are defined. This process is an iterative process whereby the image analyst chooses the proper thresholds for achieving satisfying results. The final step in this segmentation process is an automated filtering of the boundary lines of the lower left quadrant from the upper left quadrant to obtain the lower right quadrant. A zero value in all bands is assigned to the filtered out pixels resulting in the black areas shown on the lower right quadrant. Notice that the parcels resulting from the segmentation process do follow in the large majority of cases in shape and size the different field crops and that only rarely individual fields are divided in multiple sub-units.

3.2 Training

Assuming that each agglomerate of pixels within a parcel portrays a single object, which is normally the case, the segmentation process provides us with the object population needed for classification. A unique identification number is assigned to each parcel, allowing for the average color of parcels to be computed in each band. Then these vector data are displayed as a color scattergram on the video screen of an image analysis system. The analyst can either assign to the points in the scattergram identical colors to those of the corresponding parcels in the image, or any transformed color (e.g. ratios between bands). In this way the analyst is provided with the capability to a) identify visually the location of class centres by grouping together scattergram points having similar color; and b) define valid training samples, by selecting parcels located around class centres as being representative of each class. In summary, the basic advantage of the GEOCLASS approach in training is that it allows the identification of valid locations for class centres, which is the paramount factor for a successful classification.

3.3 Classification

In the last phase of the classification process a classifier is applied to extend the classification from the training samples to the entire image. The conventional approach is to carry out this final stage as if the structural context of each pixel would be of no significance. In other words, if an image is scrambled, or if we would change arbitrarily the relative position of the pixels, there would be no impact on the classification results. However, contextual considerations can be quite helpful in finding the correct classification for pixels not having a distinct signature and for boundary pixels. Boundary pixels should not be processed similarly to "pure" pixels. In a conventional system class validation is done purely on theoretical grounds. Valid classes are those for which the computation of certain statistical parameters (e.g. confusion matrix) indicates no class overlap in feature space. In this case, a high level of accuracy is expected in the final classification results. However, even samples that are not overlapping in feature space may lead to an unsatisfactory classification in terms of thematic accuracy, if these samples are not located close to class centres. Even relatively small changes in selecting training samples can significantly change

the results of classification, particularly if the maximum likelihood decision rule is used as a classifier. Let us now look at the solutions to these problems provided by GEOCLASS. The first step with GEOCLASS is the classification of the color scattergram data. This will provide a much more accurate validation of the training performed than a simple estimation of probability values in misclassification. The classification of the two-dimensional scattergram representing the entire universe of parcels precedes the classification of the corresponding image. This undertaking will allow the analyst to verify whether the classification process has indeed grouped together parcels that, according to statistical distribution criteria (cluster analysis) and color, should belong to the same class. Since a unique code number is associated with each parcel, it is feasible to cross check scattergram data with imagery data. Experimentation has shown that valid changes to the number of classes and to the training samples associated with them can be introduced at this stage by this procedure. Only when the analyst is satisfied that the scattergram data are properly classified, the actual classification of image data starts. Image data are classified in successive passes (Steffensen and Smith, 1978). In the first pass each parcel (see again the lower right quadrant of figure 1) is classified as a single class. In each of the successive passes, the individual pixels that were filtered out during the segmentation process will be also classified. Before deciding about a pixel attribution to a class or a combination of two classes (boundary pixels), reference is made to the type of already classified neighbours. The logic of this process is that, although the signature of a pixel alone would not be necessarily sufficiently distinct to determine unequivocally its thematic nature, the proximity to an already classified pixel will help in making a correct decision. To provide an example, if a "pure" pixel has a signature which is similar to two different classes but all its neighbours belong to only one of these two classes, it is most probable that the pixel in question also belongs to the same class as its neighbours, although in pure probabilistic terms it may actually belong to the other class. However, if the signature of the pixel in question would be such as to exclude the possibility that it belongs to the same class as its neighbours, the mere presence of neighbours having different attribution is not a valid reason for overruling the decision made. Unfortunately, post-classification filters widely used commercially do just this.

3.4 Classification Results

The GEOCLASS approach was tested by comparing the results of classifying the agricultural test site data of figure 1 with the results previously obtained in 1986 by Steffensen and Mack (ref.cit.) using a conventional maximum likelihood pixel-by-pixel classifier. To overcome the difficulties inherent to the multispectral classification of crop types at this early stage of growth (crops were seeded only 30 to 60 days earlier) extensive use of ground truth information (a detailed field map recording ground cover, color, growth stage, etc., for more than 100 fields) was made. Actually, all training samples were selected within the ground truth sample. The comparison of the results of classification with the ground truth map data yielded an average accuracy of 87%. This level of accuracy would have been impossible to achieve in a conventional classification without the availability of the ground truth information. In contrast, the GEOCLASS approach was applied without any reference to the ground truth data. Ground truth data were only used to assess the accuracy of the results of classification. This assessment indicated that an

equal, if not better, accuracy was obtained for each crop type previously classified with the conventional approach, and that an average accuracy of 90% was achieved.

4. CONCLUSIONS

This paper illustrates the philosophy behind the development of a new approach to the thematic classification of multispectral imagery. Instead of individual pixels, agglomerates of pixels having similar spectral and spatial attributes are the objects of classification. The key factor for a successful implementation of this methodology is the ability to subdivide any multispectral image into segments closely related to terrain features of interest. Beside the successful experiment conducted with the GEOCLASS image analysis software on an agricultural test site in Manitoba, Canada, illustrated above, a number of other agricultural areas in Canada and Europe were also successfully processed, involving not only LANDSAT-TM but also LANDSAT-MSS, MOS and SPOT images. It appears, therefore, that this innovative approach could provide universal application to agriculture. GEOCLASS was also applied to the automated identification of individual tree species using large scale (one meter pixel size) Multispectral Electro-optical Imaging Scanner (MEIS II) airborne data (Mc Coll et al., 1983). The scene used was acquired on Oct.29, 1985 over the Petawawa National Forestry Institute research forest located near Chalk River, Ontario. Using the GEOCLASS segmentation algorithm, the central portions of individual tree crowns of Red Pine, White Pine, White Spruce, Red Spruce and Norway Spruce occurring in pure and mixed stands with open to dense crown closures were successfully isolated. The filtering out of the crown portion mostly affected by large variations in reflectance, i.e. the rim, eliminates an unavoidable source of error in pixel-by-pixel classification. Without having access to a precise ground truth that would provide species identification tree by tree, accuracy figures cannot be quoted. However, preliminary classification results indicate that higher classification accuracies can be obtained with GEOCLASS than with any other conventional approach.

5. REFERENCES

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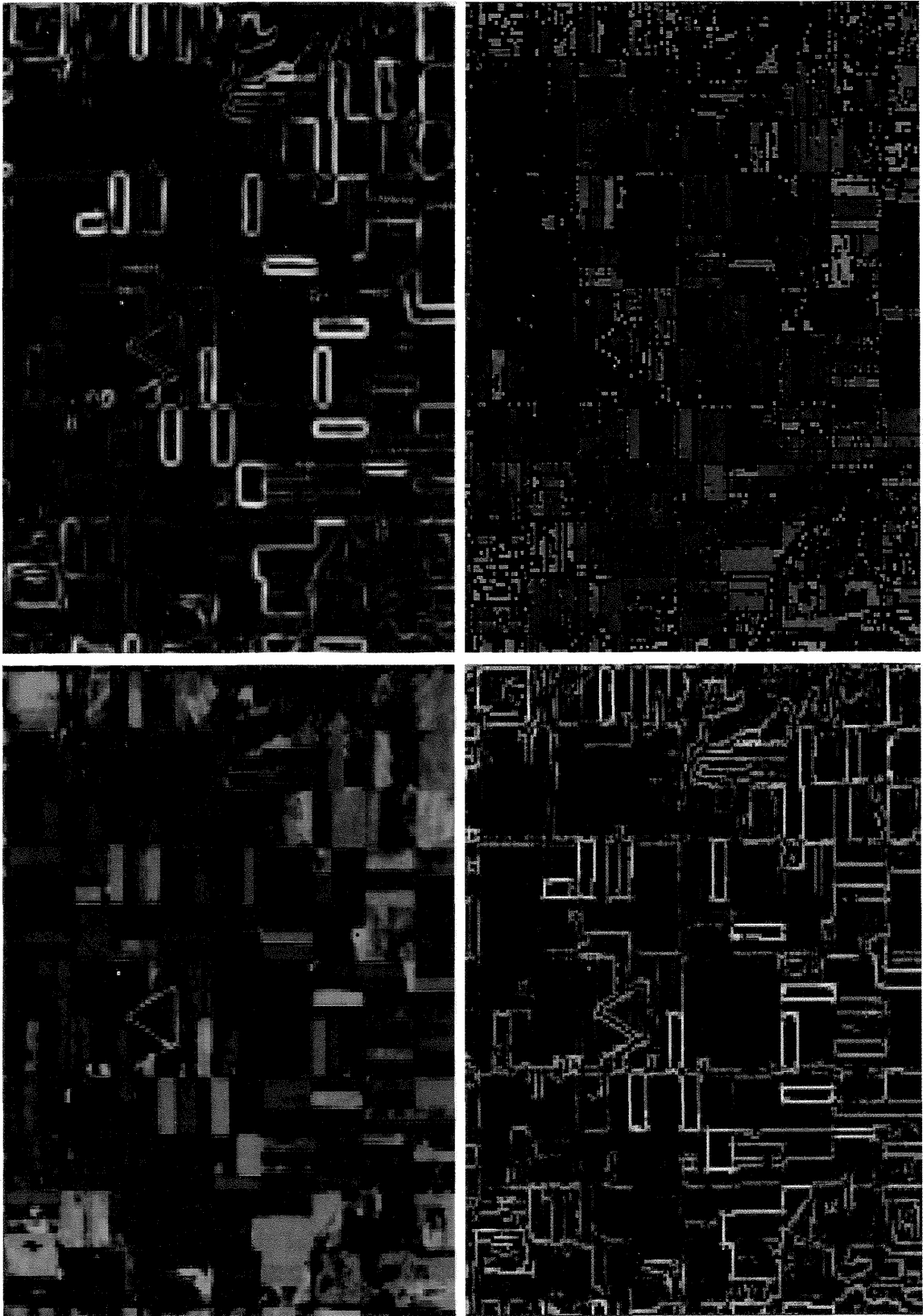


Fig. 1 - GEOCLASS Image Segmentation Process