INTERNATIONAL SOCIETY FOR PHOTOGRAMMETRY AND REMOTE SENSING
XVth Congress, Rio de Janeiro 1984 - Invited Paper

Trends and developments in the classification of multispectral data

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Commission VII

Abstract

The use of multitemporal data, the correction of systematic effects and the consideration of collateral date, e.g. a digital terrain model has improved classification performance considerable. With new high resolution spaceborne systems the vicinity of the individual pixels must be included in the evaluation. Typical approaches in statistical texture analysis, structural texture analysis and the evaluation of context are reviewed. The combination of these techniques is demonstrated and major areas for further activities identified.

1. Introduction

The classification of multispectral remote sensing data became more and more important within the last 12 years. Supervised and unsupervised classification of Landsat data is widely used, e.g. for landuse mapping and agricultural and forestry inventories in many countries. In the differentiation and mapping of crop types significant improvements were achieved with multitemporal data, e.g. through the development of temporal- spectral profiles (e.g. Crist & Malila, 1980). The consideration of systematic effects, e.g. directional reflectance properties in airborne data, results also in better classifications (Pfeiffer, 1983).

To improve classification results further collateral information, which is not contained in the remote sensing data, can be included in the evaluation procedure. Two types of collateral information should be distinguished:

1. "maplike" information, e.g. a digital terrain model or soils map
2. general or specific rules establishing a relationship between available data - remote sensing or collateral - and the classes or effects to be determined.

For example Strahler (1981) and Hoffer et al. (1979) determined by sampling in the field the tree species distribution with altitude, slope and aspect. They used this information in combination with Landsat data and a digital terrain model to produce a more detailed forest cover map. Two of the different approaches are discussed. Strahler (1981) calculated for each pixel the a priori probability of the different tree species, based on altitude,slope and aspect, extracted from the digital terrain model, and the statistical species distribution. This pixel dependant a priori probability was then used in a standard maximum likelihood classification.

Hoffer et al. (1979) employed a layered classifier. In the first step coniferous forest,decidious forest,water,meadows and bare rock were classified with the multispectral Landsat data alone. In the second step each vegetation class was subdivided based on the statistical probability for species groups to occour at the altitude of the pixel, extracted again from the DTM. Similarly DTM data were used e.g. by Hoffer et al. (1979) to correct the illumination differences in Landsat data due to topography.

2. Need to include texture and context in the evaluation

With all these techniques only a limited amount of the information contained in remote sensing data - the spectral information for individual pixels - is used. Experience in photointerpretation has shown that texture, pattern, shape, size, position and shadow contribute significantly to the information which can be extracted from images. To use this information it is not sufficient to evaluate each pixel separately but the vicinity or neighbourhood of each pixel must be considered. In some cases it may be necessary to evaluate the spatial arrangement of classes in the complete image.

With the relatively low resolution of 80 meters for Landsat data and the lack of suitable evaluation procedures this was not to important in the past.But with the much better resolution of the new spaceborne data - Thematic Mapper with 30 m and SPOT with 20 and 10 m resolution - the neighbourhood has to be considered for many applications (see Townshend & Justice, 1981). Furthermore a new generation of airborne scanners with CCD arrays could expand the application of digital image processing in remote sensing dramatically. It is therefore worthwile to discuss major evaluation possibilities more in detail. The techniques can be grouped under the keywords

1. statistical texture analysis
2. structural texture analysis
3. evaluation of context

Often it is necessary to combine different techniques, e.g. spectral and textural analysis to achieve good results as some examples will demonstrate.

An interesting new approach is the use of multiresolution images (Rosenfeld, 1984). For example in an image pyramid each higher level is created by averaging the intensities in nonoverlapping 2 x 2 blocks of pixels. These images stacked on top of one another constitute an exponentially tapering pyramid of images. This data structure offers interesting possibilities to evaluate local and regional information, e.g. texture. A quad tree is another form of multiresolution image with a more complex internal structure and is discussed more in detail in chapter 5.

Unfortunately only a few comparisons exist for remote sensing applications of the different techniques (e.g. Weszka et al., 1976, Bargel, 1983).Furthermore many procedures were reported with new data, making it very difficult to judge if they are really better than existing techniques. The suitability of different approaches depends very much on the data type, scale or resolution and the application problem to be solved. In addition minor details of the procedure, the evaluated data or the classes can have a significant effect on the performance.Nevertheless it is attempted to give a subjective overview of major techniques and their general suitability for remote sensing applications.

3. Statistical texture analysis

In statistical texture analysis statistical properties are calculated for all pixels contained in raster cells or segments.Haralick (1978, 1979) gives a good review of the many techniques. The definition of the segments or the raster size is critical. In a regular grid the raster cell boundaries often do not coincide with texture boundaries, resulting in cells with two or more different textures. One of the main problems is therefore the selection of a suitable cell size, which should be large enough to describe the texture properly, but also so small that only one texture class is contained within a cell.Possibilities to solve this problem are the use of different raster sizes or the segmentation of the image as a first step, based for example on a structural texture analysis (see chapter 4 and 5).

Fourier analysis yields information about the orientation and spatial frequency of brightness changes in raster cells. It is useful to separate major groups e.g. settlement and large agricultural fields, characterized by a more or less regularly arranged pattern of objects. Smaller differences, e.g. between decidious forest of different age or settlement types are difficult to detect (Bargel, 1983). Furthermore computing time is fairly high.

Haralick et al. (1973) suggested co-occurrence matrices to characterize texture. A co-occurrence matrix describes how often combinations of brightness levels occour for pairs of pixels with a given spatial relationship e.g. horizontal neighbours. Based on the co-occurrence matrix Haralick et al. defined 14 statistical values e.g. mean, contrast and entropy to characterize texture. The co-occurrence matrices can be calculated for different distances and orientations between pixel pairs resulting in many texture features.

Weszka et al. (1976) developed texture features based on histograms of the absolute difference of pixel pairs with a given spatial relationship. Their features are computationally less demanding than the Haralick parameters. Weszka et al. studied the influence of orientation and distance of the pixel pairs on the separation of classes for their features and the Haralick parameters and features extracted from a Fourier analysis. Their study is still very interesting and provides some important insights.

They used two different data sets. One set with 9 different classes (Urban, suburban, lake, woods, scrub, railroad, swamp, marsh and orchard) consisted of 6 samples with 64 x 64 pixels per class taken from large scale black and white aerial photographs. The second set consisted of 3 different terrain types associated with 3 flatlying rock types.Each terrain type was represented by 60 samples with 64 x 64 pixels from Landsat data and the visual inspection shows that the differences between the three types are much smaller than in the first set.

For the first set the contrast in the co-occurrence matrix and the mean for the difference histogram was calculated for the 16 combinations of 4 directions - horizontal, vertical and the two diagonals - and 4 distances (1,2,4,8 pixels). In addition one feature for the 16 intersections of 4 rings and 4 wedges in a Fourier power spectrum were used. For pairs of features the first order statistics of the difference histograms performed slightly better (43 out of 54 correctly classified) than the second order statistics of the co-occurrence matrix (40) and the Fourier analysis slightly worse (38).Consistently for all 3 methods a combination of two distances in the same direction performed best. This could be the effect of strong diagonal elements in some samples. Furthermore a combination with a very small distance (1 or 2) and a longer distance (4 or 8) often in the same direction yielded good results, which were nearly equal for a number of combinations.

With the second data set similar results were achieved.Texture features based on the cooccurence matrices and the difference histograms performed equally well and Fourier analysis gave worse results. Here short distances (1 or 2) but with different directions performed best. Other features and averaging the vicinity of pixels before the texture features are calculated were also evaluated. The computationally cheapest of the investigated statistical features, that is the means of single point difference histograms,performed as well as the other features. Therefore there should be no loss in classification power in using this feature. Depending on the data to be evaluated direction or distance are important.

More recently Pietikainen et al. (1983) applied "texture energy measures" developed by Laws to two of the terrain samples of the second data set. Laws properties are basically developed from combinations of three simple vectors for center weighted local averages, edge detection and spot detection. At least for certain data they perform better than the difference measures discussed above.

Hsu (1978) calculated texture features in very small windows (3 x 3 or 5 x 5) and classified the central pixel with this information. Features are e.g. mean, standard deviation, mean contrast of the central pixel to its neighbours and the area above and below datum planes of 50, 100 and 150. He achieved 85 to 90 percent accuracy for general land use types using panchromatic aerial photographs digitized to a resolution of about 2.5 and 17 m. Applying essentially the same features to Landsat data with 80 m resolution Irons & Petersen (1981) did not achieve useful results. This emphasizes the fact that resolution or scale is very critical in using texture analysis.

Other features are discussed in the literature (e.g. Haralick, 1978, 1979, Bargel, 1983, Pietikainen & Rosenfeld, 1982) but their general usefulness is not yet established. Often the selection of appropriate control parameters, e.g. gray level intervals, is difficult, the parameters are sensitive to noisy data or just do not contain enough information for a more detailed analysis (Bargel,1983).

All of these statistical texture features evaluate only black and white images or one band at a time. True multispectral texture features, describing colour changes and not just brightness changes are rarely used. Textures based on ratio images or the covariance of two channels in a raster cell are very simple multispectral texture features. Rosenfeld et al. (1982) suggest absolute difference distributions in two bands similar to the co-occurrence matrix to characterize multispectral texture. Sometimes they yield better results than single band features.

4. Structural texture analysis

In structural texture analysis the spatial arrangement of texture elements or primitives is studied.Consequently two steps are essential:

1. Definition of texture primitives, which can be caracterized by colour,size and shape.
2. Determination of spatial arrangements, e.g. the typical distance between primitives.

To define primitives cluster techniques are often used to create classes of spectrally similar pixels. Adjoining pixels of the same spectral class are then grouped together and if they form regions of similar shape or size define one set of texture primitives. Then distance transformations or special graphs, e.g. a minimal spanning tree, are applied to determine typical distances (e.g. Pavlidis, 1977). All primitives which can be connected by distances not longer than this typical distance form a texture segment. An example in the next chapter explains the general idea.

The notion of texture hierarchy (e.g. Desachy & Castan, 1982) is an interesting extension. Texture segments again could be primitives for the next hierarchy level of textures, defining a more global relationship.

5.Combination of spectral and textural information

Classifications based on either spectral or textural features alone can be quite successfull for specific data and applications. Both feature sets are complimentary and therefore their combination should improve classification results in many cases significantly. Furthermore more flexible classification procedures can be developed.

Already one year after the launch of Landsat 1 Haralick et al. (1973) combined texture parameters based on the co-occurrence matrix with spectral features to separate coastal forests, woodlands, annual grassland, small irrigated fields and large irrigated fields in Landsat data.

The ECHO (extraction and classification of homogeneous objects) classifier developed by LARS (Kettig & Landgrebe, 1976) presented a different method. Here statistical tests are used to find homogeneous regions, which often correspond to agricultural fields. Each region is then classified using a maximum likelihood sample classification rule.

Two recent examples of very different approaches demonstrate the basic ideas and possibilities to combine spectral and textural information in an evaluation procedure.

The "Forschungsinstitut für Informationsverarbeitung und Mustererkennung (FIM)" is developing a system to evaluate multispectral remote sensing data automatically without human interaction (Mauer & Schärf, 1982, 1983). The evaluation consists of a sequence of procedures and the results of the preceeding steps determine and control the next step. The system was tested with images of airborne scanner data from Germany with a resolution of approximately 4 m. A contrast detection algorithm distinguishes between high and low contrast areas. Low contrast areas of sufficient size indicate homogeneous areas. They are used as automatically detected training areas and are fused into classes, if their spectral properties are similar. Then e.g. a maximum likelihood classification is performed for the complete image . All pixels which were threshholded and not assigned to a class in the classification are included in a cluster analysis . The resulting spectral classes together with the classes obtained through the maximum likelihood classification yield a complete automatic multispectral classification of the image.

Only larger compact areas with the same class assignment in the maximum likelihood classification and without pixels of other classes are considered reliable final results. All other areas are included in a structural texture analysis. Three different approaches are used. Through shape analysis linear spectrally homogeneous regions are identified, which form the starting points for line extraction algorithms e.g. to detect roads.

In other areas pixels of the same spectral class, that is one type of texture elements, are adjacent and form larger continous areas which contain other classes. This not compact homogeneous regions indicate a texture with a spectrally homogeneous background . For each of this regions a statistical texture analysis in a raster is performed to verify a uniform texture. Then the different non compact homogeneous regions are superimposed to define texture segments.

The remaining spectral classes mainly form small spectrally homogeneous regions which are potential texture primitives. For each class of these texture candidates the distances between adjacent elements are investigated to define those areas which can be characterized by a typical distance between primitives. Again these areas are superimposed and form a second set of texture segments. For all these segments a statistical texture analysis is performed. Considering the adjacency segments with similar textures are combined. In the final result major classes are seperated, which can be labeled as villages, forests, rivers and different agricultural fields. In a data set without large homogeneous objects a statistical texture analysis in a raster could be the first step.

Characteristic for this approach is:

1. The alternation of spectral and textural analysis steps to combine the advantages of the different procedures.
2. The sequence and the areas to be evaluated are controlled by the data and the already achieved results.
3. No interaction is required and a completely automatic evaluation is possible.
4. Simple procedures are used first and complex algorithms are only applied to a subset of data.

In a last step the user has to interpret and label the classes, which are separated by the analysis procedure without any a priori information. The spectral and textural properties of the classes as well as their position and distribution within the scene should allow an experienced user a meaningful description of the classes, e.g. as suburban areas. This approach could be compared with the "unsupervised" clustering techniques in a pure multispectral classification.

Haberäcker & Thiemann (1983) developed at IABG an evaluation procedure based on a quad tree image structure. In a quad tree an image is divided in four quadrants. Each quadrant is again subdivided in 4 smaller quads called sons and so on, until in the last level a quad consists of only one pixel. For each of these quads or nodes statistical values are calculated, e.g. the mean, minimum and maximum of all pixels in the quad. If the difference between minimum and maximum is smaller than a threshhold, this quad is not subdivided and indicates a homogeneous region. A high number of descendants that is sons, grandsons etc. within a quad characterizes a texture in this region.

In this system specific procedures are applied to extract classes. To identify water as the first step all homogeneous quads are classified with a maximum likelihood decision rule. For nodes of a given minimal level, classified as water, the adjacent nodes are searched to determine the precise boundaries of the lake. Nodes recognized as water,but not yet connected with lakes, are the starting points for a line following algorithm to detect creeks and rivers.

The total number of descendants for a node of level 4 (that is 16 x 16 pixels) is used to identify inhomogeneous, possibly forested areas. The co-occurrence matrix for these nodes is calculated and compared with the co-occurrence matrices of different forest classes using a modified chi square test. For nodes accepted as forest a multispectral classifcation is performed and detection of the forest boundaries follows. Nodes not passing the chi square test indicate other structured areas. They can be caused by roads, which are detected with a line following algorithm.

Here a significant amount of experience is incorporated in the design of the evaluation procedure, resulting in a specific sequence to identify predetermined classes. This approach could be compared with a "supervised" multispectral classification. It may be appropriate if similar data are used. A change in resolution, e.g. from 4 meters in the example to 40 m for a satellite system could require a substantial redesign of the classification sequence and a selection of other characteristic features to identify classes.

6. Evaluation of context

Context can be a very efficient tool to identify objects. For example boats and cars can be separated using context, even if they have the same spectral properties. All possible boats/cars surrounded by pixels classified as water are labeled boats, those surrounded by roads are labeled cars. Misclassification would occour if a boat is on a trailer on a road.

This basic idea can be employed in two different ways:

1. Considering context during classification.
2. Using context in the postprocessing of classification results.

Welch & Salter (1971) laid the basic foundations for contextual image pattern classification. They used compound decision theory, which is applicable if the same decision has to be made n times, e.g. for each pixel. In theory all pixels or cells in the image should be considered simultaneously, but in most cases only the adjacent 4 or 8 pixels are evaluated. The class transition probabilities are used to describe context, that is the probability that a pixel belong to a class, if the adjacent pixels belong to given classes. In most cases the classes of the neighbouring pixels are not known and must be estimated using e.g. the spectral properties of these pixels. Welch & Salter used simulations with 22 categories taken from aerial photographs to test their procedures and found a significant improvement using context with the 4 immediate neighbours.

Similar approaches are discussed by Swain et al (1980). Yu and Fu (1983) used a spatial stochastic model which is characterized by a spatial correlation parameter. The resulting recursive contextual classification was tested with Landsat data and improved classification accuracies in residential and agricultural/forested areas significantly. Only for commercial areas and golf courses the classification accuracy decreased. Lumia et al. (1983) applied image segmentation in aerial photographs to define units, which were assigned to cluster types. Based on the cluster types of adjacent units texture classes were formed.

Computationally less demanding is the postprocessing of classification results using context. The simplest form is the cleanup of classification results, e.g. to reassign a pixel classified as class X to class Y, if a predetermined number of adjacent pixels are classified as Y (e.g. Todd et al., 1980, Scarpace et al., 1981). If great windows are used, a considerable generalization can be achieved (Gurney, 1981). Itten (1980) employed class specific patterns and Thomas (1980) a proximity function, giving more distant pixels less weight in the decision. Gurney & Townshend (1983) used the direction and distance between clouds and cloud shadows as context information.

A characteristic combination of classes in an area allows class assignments on a higher level. A combination of the classes street, roof, trees and grass could characterize a suburban area, the combination of trees and grass in a downtown area a small park. Shih & Schowengerdt (1983) used typical combinations of land cover to seperate geomorphological units they could not differentiate spectrally.

Flouzat (1982) followed another reasoning to determine poplar stands in Landsat data. He used context to determine all pixels classified as decidious trees, which lay within large continous areas of this class adjacent to rivers. All pixels meeting these requirements were labeled poplar since under the climatic condition in that region only near rivers the steady supply of groundwater needed by poplars is guaranteed.

7. Conclusions and recommendations

1. Many different procedures were developed in the last years to evaluate spectral, textural and context information in remote sensing data and to combine them with collateral data. The tools are available.
2. The gap between photointerpretation and the possibilities of digital image analysis is decreasing. The experience already acquired in photointerpretation should be more considered in digital image analysis.
3. It is difficult or time consuming to supply the additional information required by many new techniques.
4. There is a trend from general techniques to the use of specific collateral information. The involvement of the application scientist is mandatory.
5. The usefulness and limitations of different techniques should be investigated and compared more thoroughly.
6. The experience gained with different techniques should be collected and distributed more efficiently to facilitate and expedite the application of the methods on a worldwide basis.
7. Suitable procedures or sequences of techniques and parameter settings should be determined for different data types and/or applications.
8. The effort for the training phase and the selection of

appropriate procedures must be reduced drastically for operationel applications. To achieve this goal the relationship between the features which can be extracted from remote sensing data and the desired information must be better understood. Basic research is still urgently needed.

9. The experience gained for specific applications on a regional level should be incorporated in an expert system. With the feedback from new experiments or data sets it should be possible to slowly proceed to better estimates of the characteristic values for given classes in a new data set. This information could then be used for new projects to eliminate most of the training phase or to label cluster classes automatically. This could be regarded as a numerical equivalent to a photointerpretation key.

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