EGIS'90

Proceedings

FIRST EUROPEAN CONFERENCE ON
GEOGRAPHICAL INFORMATION SYSTEMS

AMSTERDAM, THE NETHERLANDS

April 10-13, 1990

Editors:

JANJAAP HARTS
HENK F.L. OTTENS
HENK J. SCHOLTEN

Excecutive editor:

DEBY A. ONDAATJE

VOLUME 2

EGIS FOUNDATION, UTRECHT, THE NETHERLANDS

MULTI-LAYERED MODEL OF SPECTRAL, TEXTURAL AND CONTEXTUAL FEATURES FOR PIXEL LABELLING

C. Kontoes
Commission of the European Communities, Joint Research Centre,
L.I.P, T.P 670, I-21020 Ispra (Va), Italy

ABSTRACT
In order to improve the low level accuracy of the first classification attempt, special emphasis has been placed on textural features related to SPOT imagery and contextual analysis methods based on supervised relaxation techniques. A systematic study of texture parameters extracted from grey level co-occurrence matrices that refer to a sample of 43 ground truth segments, suggests the use of variance for the classification of an area into four general land use classes. Four layers comprising of the classification map of SPOT data, the probability layer of correct classification, the classification map of variance and its associated probability layer, were integrated within a spatial model which describes the label consistency in the neighbourhood of the pixel. The application of the model resulted in a post classification free of noise. Two factors which play an important role in noise removal are the number of iterations and the degree of confidence in the auxiliary data.

1. INTRODUCTION

The requirements of the C.E.C for the production of agricultural statistics on the main crop types present throughout the European Communities on a yearly basis, make indispensable the use of high resolution satellite data, because the latter provide precise and instantaneous land use mapping for large areas. At the same time, the employment of dynamic computer systems is considered necessary in order to handle diverse and large data sets and carry out the appropriate data processing. The possibility of performing complex mathematic and algorithmic operations on the data, does not necessarily mean the production of more accurate agricultural statistics and land use thematic maps, because the latter are highly depended on the entry data substance and quality. In fact, a pixel based classification, which has been carried out using raw SPOT data, covering the Loire et Cher region in central France, supervised by the use of 65 ground truth sampled segments, resulted in many residual inaccuracies and class ambiguities. The overall statistical classification accuracy achieved equals 50.06%. Only in a later classification, after the entry data have been pre-processed by the Nagao-Matsuyama edge preserving smoothing filter, an almost admissible statistical accuracy of 65.67% has been reached. However, thematic inaccuracies still remain since isolated misclassified pixels are scattered throughout homogeneous land use classes and class borders comprise of eroded lines, providing low separation between adjacent and different object types, from a thematic point of view. The present study aims to derive additional sources of land use information and to develop the appropriate methodology of using them, in order to reduce the inaccuracies mentioned above, in a post classification level process.

2. TEXTURE FEATURES AND LAND USE STRATIFICATION

2.1 Previous work

A common analysis of the information stated on a satellite scene refers to spectral, spatial and temporal variations of the energy distribution. In the present study the aspect "temporal" is not considered, because only the single date scene processing matches the requirements for fast and timely estimations of crop acreages over the European Communities. In contrast, the study of the spatial relationships of the tonal variations within the scene, has been considered indispensable, in order to discriminate among objects with the same radiometry but different textural qualities. A good review of various texture analysis methods may be found in (Vilnrotter F., 1986), (Haralick R., 1979), (Weszka J., 1976). Early studies have employed auto-correlation functions, (Kaizer H., 1955), optical processing methods (O'Neill E., 1956) or digital transforms of the image, like Fourier transform, (Bajcsy R. et al., 1976), where texture is expressed in terms of directionality and periodicity. Conners and Harlow (1980) make use of the grey level run length, where the grey tone of the run, the length of the run, the direction of the run and the distribution of the run, describe the texture properties of the image. Structural approaches to texture appeared more recently. Some interesting experiments for defining texture using structural primitives (pixels, grey level peaks, line segments) may be found in (Laws K., 1980), (Carlucci A., 1972) and (Argialas D., 1988). For the purposes of the present study, the emphasis has been placed on statistical measurements of texture, given by a vector of numbers rather than symbolic or structural descriptions. A set of such measurements has been introduced by Haralick et al. (Haralick R., 1973) and relates to properties of the image like homogeneity, grey tone linear dependencies, local radiometric variability, image structure complexity e.t.c. The technique proposed for the computations uses the angular nearest neighbour grey tone spatial dependence matrices or "co-occurrence matrices". Haralick proposed a set of 28 texture features. Four of them were selected for the needs of the current study:

a) The Angular Second Moment, which is a measure of the homogeneity characterizing the image and given by the following formula,

$$ASM = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (P_{ij}/R)^2 \qquad \text{where,}$$

Ng is the number of the grey tones in which the image is quantized; P_{ij} is an element of the grey tone spatial dependence matrix and R is a normalization factor representing the number of possible neighbouring cells.

b) The contrast feature is a measure of the local variations present on the image plane given by:

$$CON = \sum_{n=0}^{Ng-1} n^2 \left[\sum_{|i-j|=n} (P_{ij}/R) \right]$$

c) The correlation feature, is a measure of grey tone linear dependencies. It is given by the formula,

$$COR = \left[\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} ij\,(P_{ij}/R) - \mu_x \mu_y \right] / \sigma_x \sigma_y \qquad \text{where,}$$

the quantities $\mu_x, \mu_y, \sigma_x, \sigma_y$ are the means and standard deviations respectively of the marginal distributions associated with the elements of the grey tone spatial dependence matrix.

d) The Sum of Squares or Variance, provides information related to the complexity of the image structure. It is expressed by the following formula:

$$VAR = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (i-j)^2 P_{ij} / R$$

These four features were used in order to aid the classification of the multispectral SPOT data.

2.2 Experiment

Multispectral SPOT data obtained on May 1, 1986 has been used for texture analysis. The dataset consist of three scenes of 1.b pre-processing level, covering the Loire et Cher department in central France. Channel 3 has been selected for texture computations, since its properties of chlorophyll absorption, strong leaf scattering and water absorption, are very important in terms of texture analysis, while they provide a considerable grey tone variability. Different sizes of resolution cells drawn from the set {3, 7, 10, 15} were selected for the computations. Five distinct displacement values d = {1, 3, 5, 7, 9} and two types of radiometric data, including raw SPOT XS and filtered SPOT XS (using N-M Edge Preserving Smoothing Filter) have been used in order to compare the effects of the displacement size and data type on the results. Texture signatures were extracted for all of the 15 most important crop types present throughout the study region using a set of 43 ground truth segments which make up a representative sample in terms of agriculture and socioeconomic conditions. The results; the variance feature computed from raw data using a 10x10 resolution cell displaced by 1, may be used for the extraction of signatures which describe four distinct land use classes, with respect to the SWAIN-FU distance separability criterion (SWAIN P. et al., 1972), see Fig. 1. Land use classes contain crop types, as follows:

Land Use class No. 1. (Agriculture & Horticulture): wheat, barley, sunflower, rape seeds, other.

Land Use class No. 2. (Agriculture & Urban): pasture, permanent pasture, maize, vineyards, oats, urban (urban vegetation, farmstead, urban).

Land Use class No. 3. (Forest): deciduous, mixed forest, conifers, resinous, poplar trees.

Land Use class No. 4. (Water): rivers, pond water, wetlands.

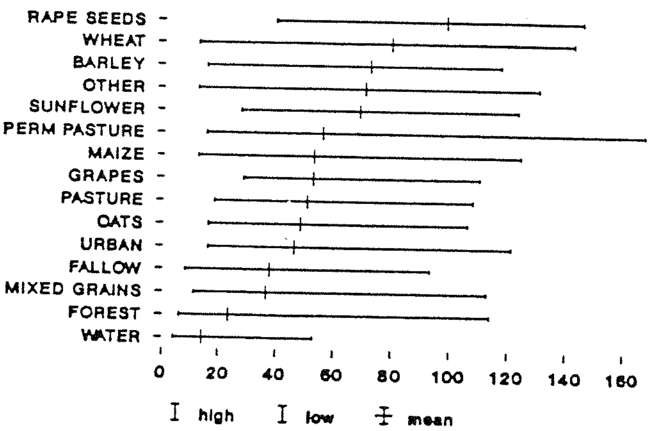

Fig. 1 Range plots for average Variance.

2.3 Land use classification based on variance signatures

In order to test the utility of variance for land use classification, two 512x512 blocks, were selected. The blocs are representative of the study area in terms of land occupation. One block is located north east of the city of Blois including vast agriculture zones, forested and urban areas. The Loire river cuts out the agriculture area into two distinct zones, in terms of crop types, field size and field orientation. Test area 2 is a part of the Grand Sologne region, mainly covered by industrial forests and pasture cultures. There is no systematic agriculture production present in the region, except for some vineyard production at the southern parts. The rest of the terrain is covered by an enormous number of lakes and wetlands. The classification of the two test areas, into four land use classes has been based both on spectral and texture signatures. Fig. 6 illustrates different cases of classification maps for the two test areas. A comparative look shows that the use of variance results in map products of higher quality. Both the statistical and the thematic accuracy of the classification has been raised while the number of misclassified pixels has decreased. Also, the class borders comprise of continuous lines which preserve the irregular shape of the objects and provide accurate thematic maps. Fig. 6 illustrates the layers of the probability level of correct classification and makes clear that when the classification is based on texture the error is 30% to 0%. In contrast, when the classification is based on spectral signatures the error is 50% to 60%.

3. COMBINED USE OF SPECTRAL TEXTURAL AND CONTEXTUAL CHARACTERISTICS

3.1 Supervised relaxation algorithm

The remainder of the study, focuses on the employment of a post classification process and aims to obtain maps of higher quality, maps that is the isolated misclassified pixels will be identified and corrected. A common technique to attain this, uses information related to the spatial context of the pixel. Different approaches have been developed in order to built up a certain knowledge about the general contextual relations present in the scene (Tomlin C., 1979), (Strahler T., 1978). This study has adopted the principles of an approach referred to as "supervised relaxation labelling" suggested by Richards J. et al. (1981). The supervised relaxation processes are iterative and heuristic approaches that extract contextual information in a scene using multi-type data characteristics. The core of the model is the probability updating rule introduced by Zucker et al. (1978) defined as

$$P_i^{n+1} = P_i^n (W_k)\, Q_i^n (W_k) \;/\; \sum_{l=1}^{m} P_i^n (W_l)\, Q_i^n (W_l)$$

where,

$P_i^n (W_k)$ denote the estimate of the probability that on the n-th iteration the pixel i has a label W_k drawn from the set of m labels $M = \{W_1, ..., W_k, ..., W_l, ..., W_m\}$ and

$$Q_i^n (W_k) = \sum_{j=1}^{J} D_{ij} \sum_{l=1}^{m} P_{ij} (W_k, W_l)\;\; P_j^n (W_l)$$

is the neighbourhood operator giving the influence of the surrounding pixels.

$P_{ij} (W_k,W_l)$ is a set of compatibility coefficients which denote an estimate of the probability that pixel i is from class W_k given that pixel j is from class W_l.

D_{ij} is a set of neighbourhood weights which satisfy, $\sum_{j=1}^{J} D_{ij} = 1$ with J equals the number of the number of the pixels in the geometric window considered as the neighbourhood of the pixel i.

It is desired that the algorithm attains a better consistency among the labels with respect to their neighbourhood and to the auxiliary data. Dependency among the labels is incorporated via the compatibility coefficients $P_{ij} (W_k,W_l)$ which have been based on the following layers of information:

a) The classification map derived from the 3 SPOT XS channels using spectral signatures related to the 15 crop types.
b) The probability layer associated to the classification map above, which provides an estimate of the probability that the label of pixel i is W_k,$(P_i (W_k))$.
c) The classification map produced by the use of variance signatures, where the label of the i-th pixel denotes the land use class it belongs. According to the description given in Section 2.1 this classification indicates the group of crop types which most likely label pixel i and its neighbourhood pixels as well.

d) The probability map associated to classification in (c) above providing an estimate of the land use label. Again, these measurements indicate how probable is the label consistency introduced by the land use map, in the surrounding of the pixel i.

The compatibility coefficients are expected to vary from place to place in the dataset. So, they are estimated over square sections with the side of 10 to 30 pixels, using a set of geometric windows which has been selected randomly through the section. The compatibility coefficients are given by the following formula:

$$P_{ij}\ (W_k,W_l) = R_{i1}\ [1+B\ (m\ R_{i2}-1)]\ R_{j1}\ [1+B\ (m\ R_{j2}-1)]$$

R_{i1}, R_{i2}, R_{j1}, R_{j2} are the appropriate likelihoods for pixels i and j estimated from the two probability layers and supervised by the land use classification map.
B, is the so-called degree of supervision; it reflects the confidence in the auxiliary data. The value of B is chosen heuristically. The flow chart of Fig. 5, illustrates a brief description of the algorithm used.

3.2 <u>Experiment</u>

In order to evaluate the performance of the supervised relaxation algorithm, the classification map A of the test area 1 (see Fig. 6) has been iterated, using the described model. Fig. 2 illustrates the evolution of the classification efficiency, as a function of the iteration number and the degree of supervision. The efficiency pertains to reported versus classified statistical RMS errors, obtained by rationing the RMS error of the 1st iteration with the RMS error of the current (n-th) iteration. The choice of the value of the degree of supervision is crucial, since it influences the results. Fig. 2 indicates that in general a larger Degree of Supervision results in higher level efficiencies and at the same time the number of required iteration (that is the nb of iterations to maximize the efficiency) decreases. However, for high values of the degree of supervision the thematic accuracy of the map is facing a deterioration phase, which starts after a certain iteration number (approximately after 5 to 6 iterations) and intensifies as the number of iterations increases. The reason is that the classifications based on higher values of degree of supervision reproduce thematically the layer of the auxiliary data (variance classification map) which is characterized by rough class borders.

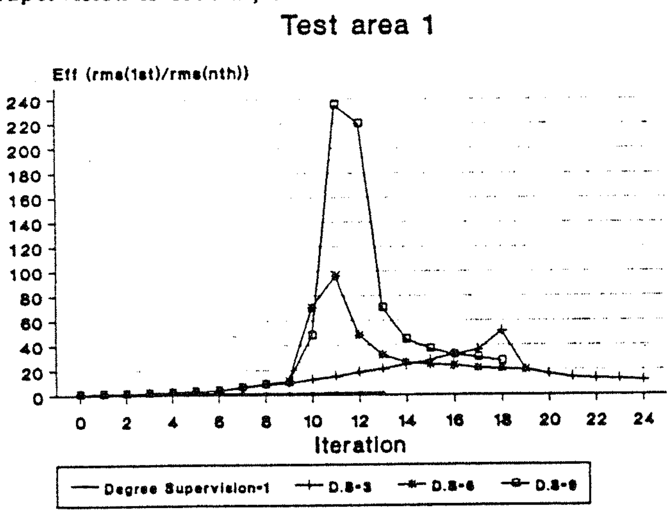

Fig. 2 Overall Classification Efficiency vs iteration Nb for D.S. = (1, 3, 6, 9).

Figs. 3 and 4 show how the statistical classification error decreases as a function of the iteration number and the degree of supervision. Fig. 7 illustrates the changes the thematic map of the test area 1 has been undergone after a certain number of iterations.

4. CONCLUSIONS

The employment of a multi-layered model which uses spectral, textural and contextual information extracted from the satellite scene, resulted in high level classification improvements by removing misclassified pixels without eroding at the same time the class

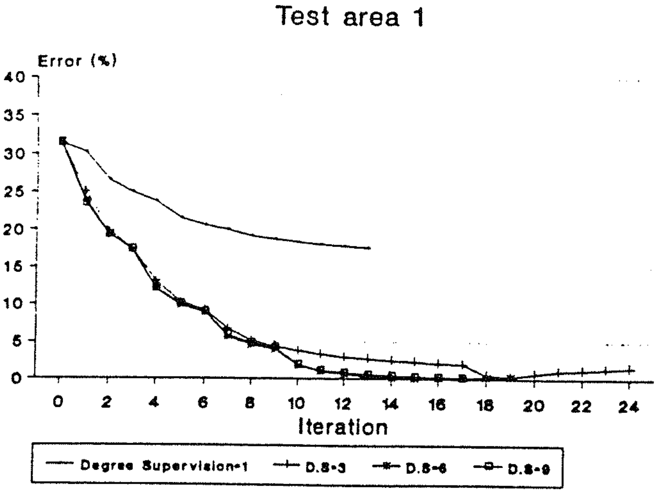

Fig. 3 Classification error (%) for Agriculture areas vs iteration Nb; D.S. = {1, 3, 6, 9}.

borders. In the current study the emphasis has been placed on the evaluation of the potential use of the supervised relaxation algorithm, for improved classifications. There are still many computational aspects to be investigated before the described model becomes of operational use.

5. ACKNOWLEDGMENTS

The suggestions of Mr. J. Stakenborg contributed significantly in realizing this research. The assistance of the department of Laboratory of Image Processing, JRC, is gratefully acknowledged.

REFERENCES

Argialas P.D. (1988), Quantitative description and classification of drainage patterns, Photogrammetric Engineering and Remote Sensing, Vol. 54, pp. 505-509.

Bajcsy R., Lieberman L. (1976), Texture gradient as a depth cue, Comput. Graph. Image Processing, Vol. 5, No. 1, pp. 52-67.

Carlucci L. (1972), A formal system for texture languages, Pattern recognition, Vol. 4, pp. 53-72.

Conners R.W., Harlow C.A. (1980), A theoretical comparison of texture algorithms, IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. PAMI-2, No. 3.

Haralick R.M., Shanmugam K., Dinstein Its'Hak (1973), Textural features for image classification, IEEE Trans. on Systems, Man, and Cybernetics, Vol. SMC-3, No. 6.

Haralick R.M. (1979), Statistical and structural approaches to texture, IEEE Proceedings, Vol. 67.

Kaizer H. (1955), A quantification of textures on aerial photographs, Boston University Research Laboratories, Boston, MA, Tech. Note 121.

Laws K. (1980), Textured image segmentation, Ph. D. dissertation, Univ. Southern California, Los Angeles, USCIPI Rep. 940.

O'Neill E. (1956), Spatial filtering in optics, IRE Trans. Inform. Theory, Vol. 2, No. 6, pp. 56-65.

Richards J.A., Landgrebe D.A., Swain P.H. (1981), Pixel labelling by supervised probabilistic relaxation, IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. PAMI-3, pp. 181-191.

Strahler A.H., Logan T.L., Bryant N.A. (1978), Improving forest classification accuracy from Landsat by incorporating topographic information, Proc. 13th Intern. Symp. Remote Sensing of the Environment, Env. Res. Ins. of Michigan, Ann Arbor. MI, pp. 927-942.

Swain P.H. (1972), Pattern Recognition, a basis for remote Sensing data analysis, LARS Information Note 11572, Purdue University, West Lafayette Indiana.

Tomlin C.D., Berry J.K. (1979), A mathematical structure for cartographic modelling in environmental analysis, Proc. Amer. Cong. Surveying and Mapping, pp. 269-283.

Vilnrotter F.M., Nevatia R., Price K.E. (1986), Structural analysis of natural textures, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. PAMI-8.

Weszka J.S., Dyer C.R., Rosenfeld A. (1976), A comparative study of texture measures for terrain classification, IEEE Transactions on Systems, Man, and Cybernetics, Vol. SMC-6 No. 4.

Zucker S.W., Mohammed J. (1978), Analysis of Probabilistic Relaxation labelling processes, Proc. IEEE Conf. Pattern Recognition and Image Processing, Chicago, IL, pp. 307-312.

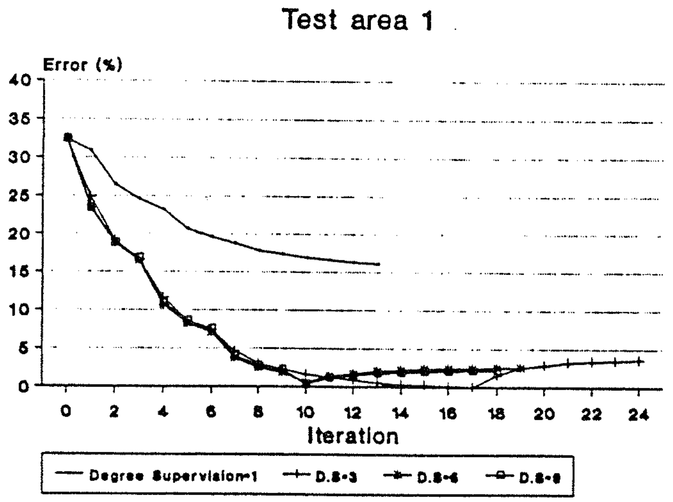

Fig. 4 Classification error (%) for forested areas vs iteration Nb; D.S. = {1, 3, 6, 9}.

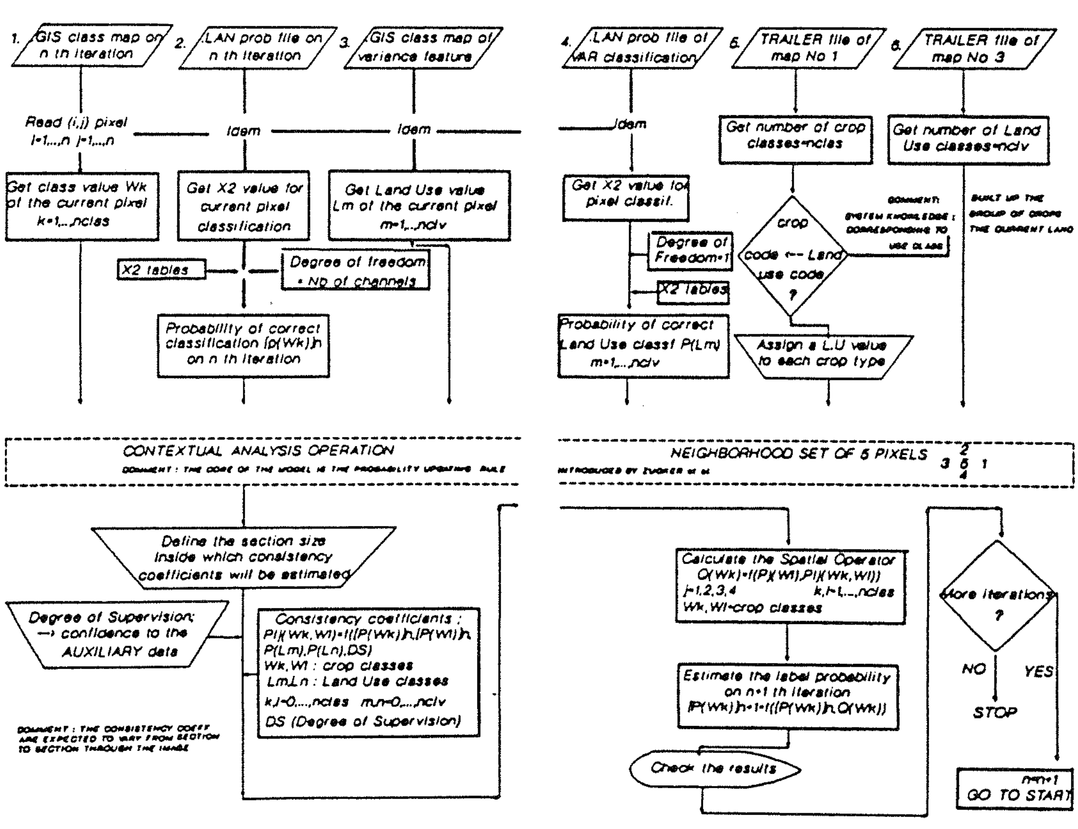

Fig. 5 Flow chart of the Supervised Relaxation Algorithm.

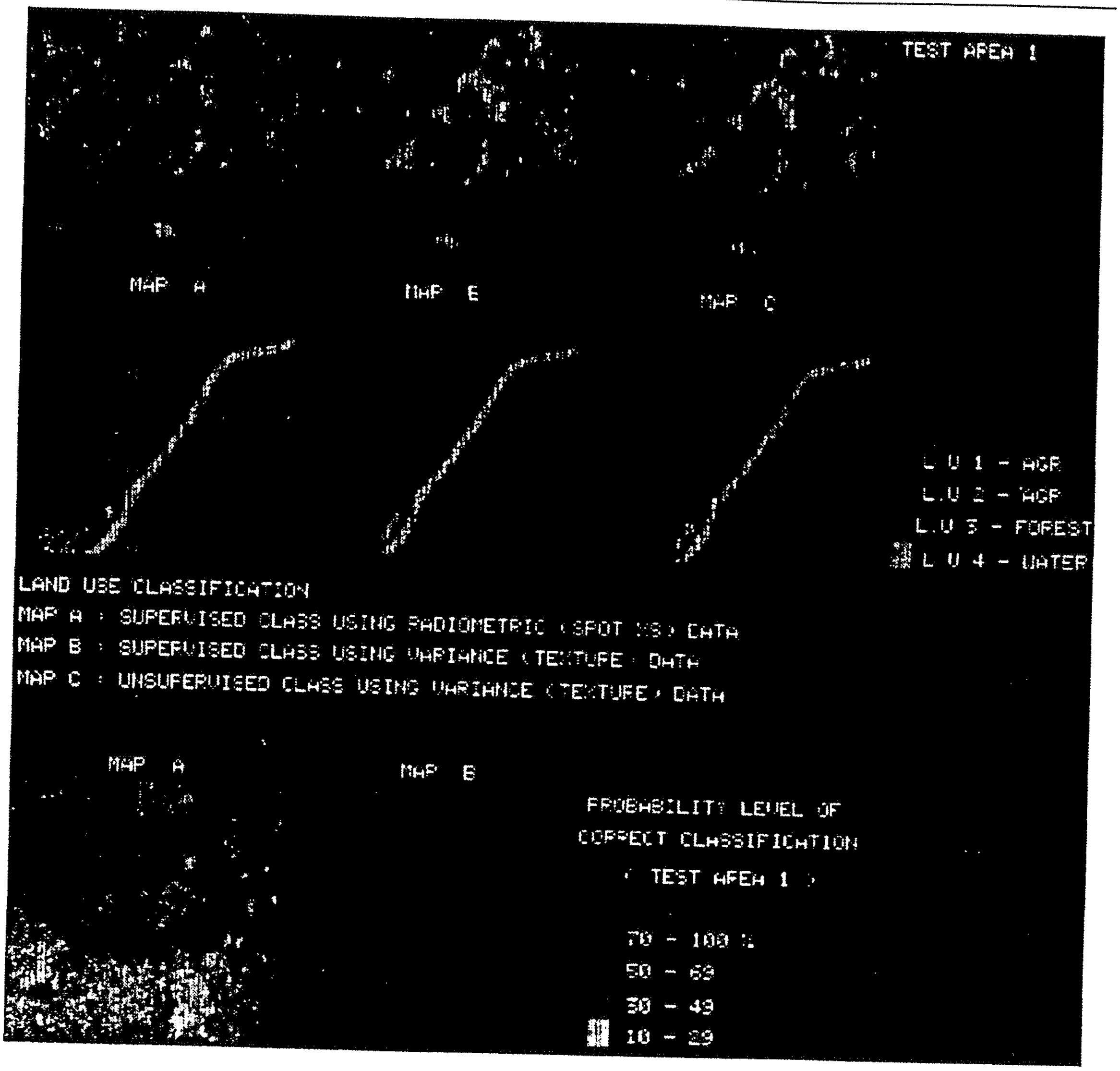

Fig. 6 Classification maps for the two test areas. Probability layers of correct classification for test area 1.

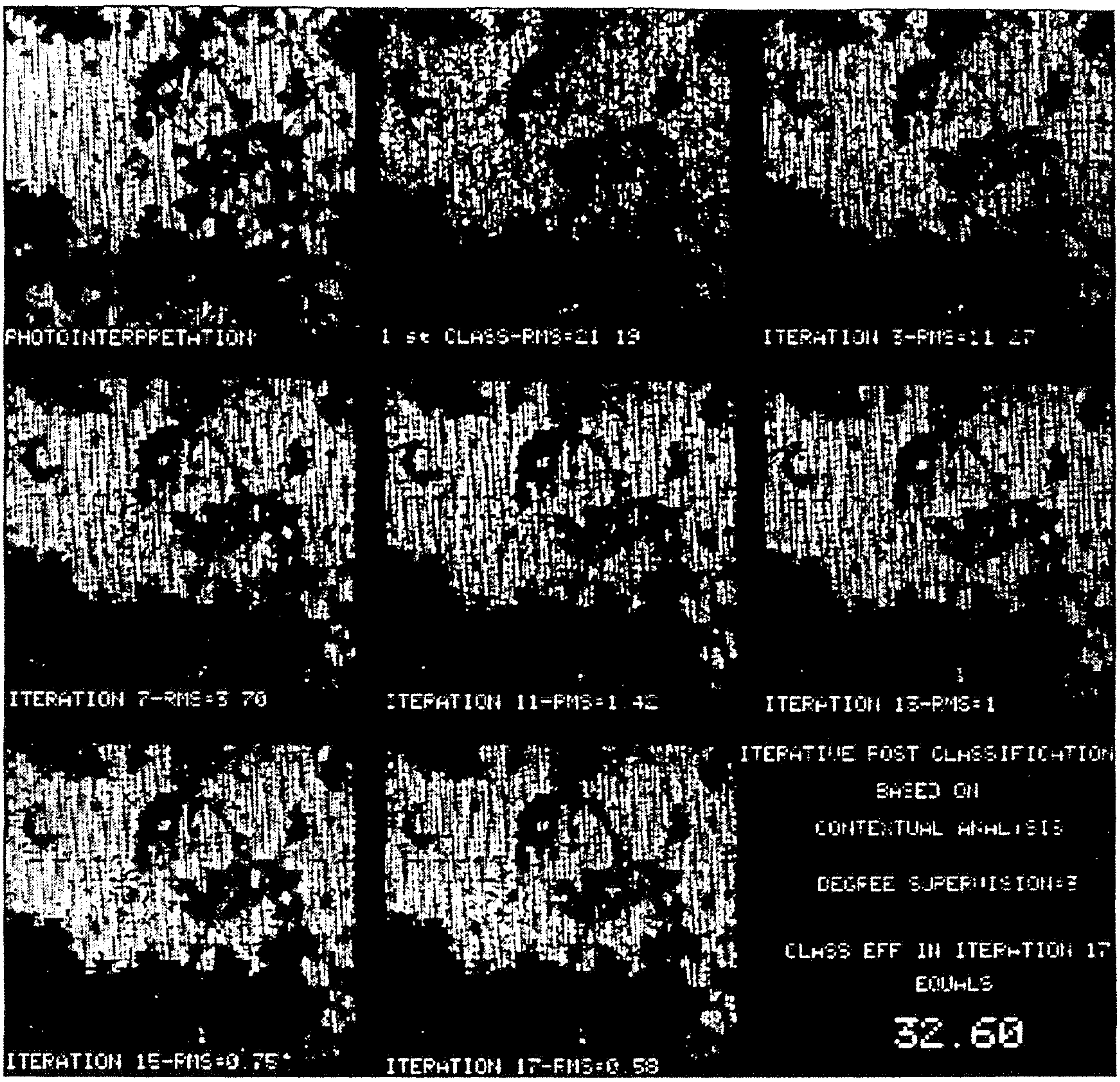

Fig. 7 Photointerpretation map, initial classification map and classification maps after a certain number of iterations, for test area 1.

IEEE Session WP-13

Knowledge Based Systems

Chair:

M. Ehlers

ITC (The Netherlands)