KNOWLEDGE BASED CLASSIFICATION OF LANDSCAPE OBJECTS COMBINING SATELLITE AND ANCILLARY DATA

Jerzy Chmiel, doctoral student, Institute of Photogrammetry and Cartography, Warsaw University of Technology, Poland, and Thomas Gumbricht, doctoral student, Division of Land and Water Resources, Royal Institute of Technology, Sweden.

KEY WORDS: Expert System, Knowledge Base, GIS, Integrated image classification, Fuzzy Logic.

ABSTRACT

The land surface pattern is related to both natural and anthropogenic processes, for which domain experts have developed corresponding semantic. Traditional image classification is based on statistical relations, disregarding qualitative relations between processes and patterns. The article presents an image classification system integrating remote sensing and georeferenced data knowledge rules inferred via a simple and transparent expert system. Performance was tested against traditional maximum likelihood classification. The expert system classification gave the best results. It is concluded that simple and transparent expert modelling can enhance understanding of spatial relations between processes and patterns, but that accuracy in georeference is crucial for inference of expert rules.

1 INTRODUCTION

The land surface is a non-random structure. The textural and structural pattern of both the natural and the cultural landscape have process derived logic (Ripl and Gumbricht, 1996). Regolith, wetness, vegetation and e.g. infrastructure are strongly interconnected and site related. Domain experts have developed corresponding object oriented semantic. However traditional image classification disregards these relations, and rely heavily on stochastic probability density functions (pdf) (cf. Argialis and Harlow, 1990). Categorisation is mostly based on procedural rules related to pixel-wise multidimensional vectors (Fig. 1). Classification accuracies have been improved by advanced statistical data modelling (e.g. Franklin and Peddle, 1989; Lauver and Whistler, 1993), by integration of multitemporal or ancillary data (e.g. Middelkoop and Jansen, 1991), and by multisource field data (e.g. Wu et al., 1988; Congalton et al., 1993; Fiorella and Ripple, 1993; Zeff and Merry, 1993). Digital elevation models (DEM) have been most widely employed. *Inter alia* used for correction of reflectance because of inclination, stratification before classification, for assigning a priori probabilities during classification, and for post processing of problematic classes.

Present developments in image classification include expert system integration, and the application of neural networks. Neural networks combine relation knowledge in hierarchical nodes, often by an inductive, backward driven iterating process. Reported successful applications include land cover classification (Hepner et al., 1990; Civco, 1993; Dreyer, 1993) and shoreline extraction (Ryan et al., 1991). However so far traditional classification methods are reported to perform equally well. Expert systems can be either inductive and backward driven, or deductive and forward (or data) driven. A recent trend has been to develop simple and transparent expert systems for integrated image classification, and domain expert languages for imprecise (fuzzy) knowledge inference (e.g. Leung and Leung, 1993; Wang, 1994). By combination with statistical discrimination classification rules can be transparently compacted (Srinisavan and Richards, 1990; Dymond and Luckman, 1994). The strong relation between landscape processes and patterns suggest that declarative knowledge rules should be powerful for integrated image classification (e.g. Skidmore et al., 1991; Gumbricht et al., 1995).

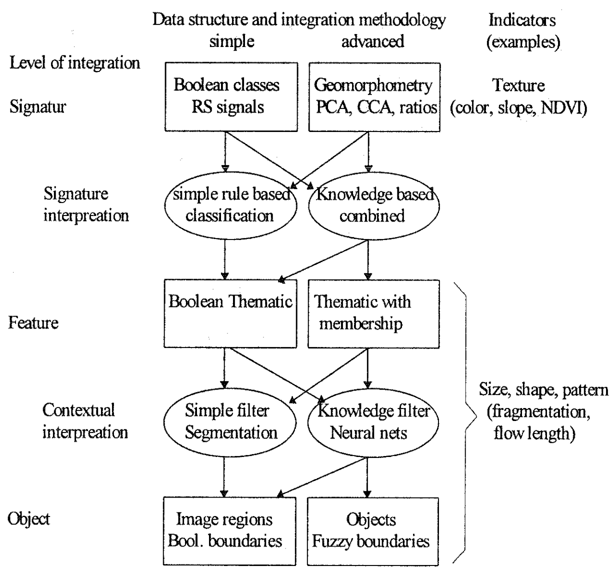

Figure 1. Simplified scheme for image classification methodologies (modified after Gumbricht et al., 1995).

This article presents a compact expert system for knowledge based image classification combining procedural and declarative knowledge representation. Its performance was compared with traditional maximum likelihood classification. The aim of the study is to define and evaluate object oriented classifications of the landscape pattern with relevance for functional management (cf. Worboys, 1994). The study is part of a larger Swedish-Polish research program aiming at defining and modelling sustainable landscape management and restitution (cf. Gumbricht, 1995).

2 STUDY AREA AND DATA SET

The studied area is the Krutynia river basin in the Great Mazurian Lake district in North East Poland (fig. 2). The data used included two Landsat TM scenes (obtained April 2nd 1990, and June 21st 1990), and manually digitised contour lines of elevation and a digitised soil map (from map scales 1:50 000). All images were transformed to a common (local) co-ordinate system (RMSE = 10 meters). Training data was created (by one of us - JC) from manual interpretation of a colour composite image made from the April data, and infra red aerial photographs (taken October 15th 1995). Ground truth data was collected (by both of us) during a field visit in May 1995. Classification and data sampling was done into 8 classes (cf. table 1).

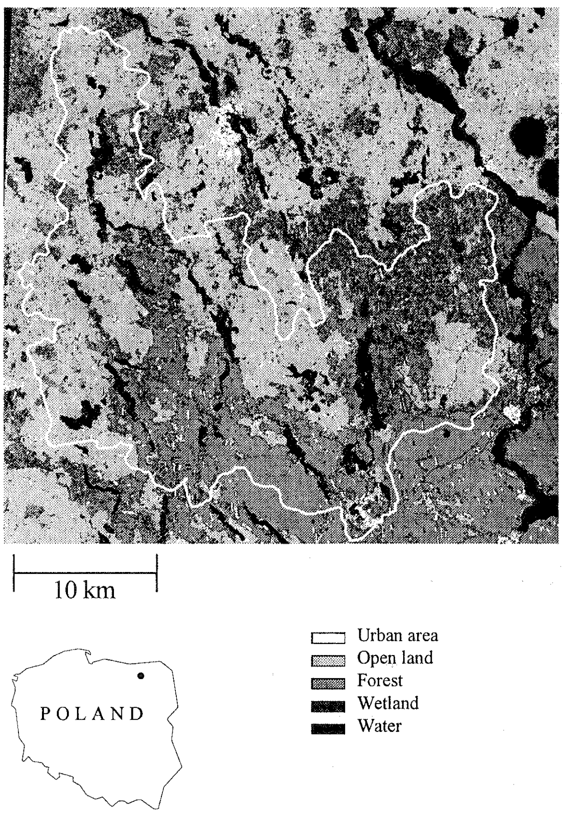

Figure 2. Study area with Krutynia river basin.

3 METHODS

Two classification methods were tested: i) a GIS integrated expert system, and ii) traditional maximum likelihood classification. The expert system is developed by one of the authors (TG), mainly as a tool for learning integrated image classification (Gumbricht, 1996). The maximum likelihood classification was done in IDRISI (Eastman, 1993).

3.1 Expert system classifier - guide

The expert system "GUIDE" is an inference tool using forward propagation (or chaining) and declarative knowledge. It can be used for both Boolean and fuzzy knowledge based classification of raster images (Fig. 3). *Guide* is supported by MS-DOS and is adapted to IDRISI format. Rules are either typed into an ascii file by the user, or automatically extracted from training data. Typically quantitative field data relations are extracted from training data, whereas object data relations (e.g. landuse and regolith symmetries) must be manually inferred by domain experts. *Guide* can handle images of different resolution, and segmentation according to positions (i.e. rows and columns of the cells).

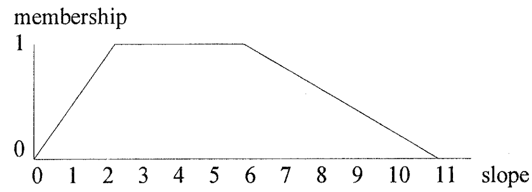

Figure 3. Example of fuzzy membership function to slope. Between slopes 2 and 6 the membership is 1, whereas it changes gradually from 0 to 1 between slope 0 and 2 and 11 and 6 respectively. In guide the above fuzzy membership function is written "Whenimg @ 0 2 TO 6 11 Slope", the Boolean logic is written "Whenimg @ 2 TO 6 Slope".

Rules are compact of the form "if condition1 ... (and condition2, and ...) then conclusion ...". Conditions are in the form of operators (=x, <x, >x, <x<), where each operator can be a vector of observations associated with the conclusion (table 1). For a conclusion to become true either the same vector observation must be true in all conditions of a single output class, or it is enough with one observation of each condition to be true. Categorisation of each output class is thus possible through a single statement, still keeping a high transparency to the user. For instance different forest classes (e.g. deciduous, coniferous) can be merged in a single rule without mixing of sub-category observations (illustrated in table 1).

In Boolean mode a pixel that has been given a value will keep this value and it can not be changed by a condition further down in the guide-file. In the fuzzy mode each cell is given a membership function (degree of belonging) associated with each output category. The category with the highest membership assigns the cell in the final output. In fuzzy mode *guide* also produces an image showing the membership function related to the assigned category for each cell. Membership function can either be cumulative (more rules give higher mf), or averaged (maximum mf = 1). The user can optionally choose to produce images of membership functions for all of the output categories. Only linear membership functions are supported (Fig. 3). If a cell does not satisfy any of the stated conditions it will remain unclassified.

Table 1. Command structure in *guide* (forest in the example can either be classified as a lumped category, or the two observations can be separately classified, making it possible to include several forest types in one rule).

command	Followed by	Example - Boolean logic	Example - fuzzy logic
WHENIMG	= category "map"	= 3 4 soil	= 3 4 soil
	< category "map"	> 0 300 DEM	>0 40 300 500 DEM
	> category "map"	< 30 20 slope	< 50 30 30 20 slope
	@ category TO category "map"	@ 10 TO 40 20 TO 30 LAI	@ 0 10 TO 40 50 10 20 TO 30 40 LAI
	+ row nr TO row nr	+ 0 TO 150 100 TO 250	+ 0 0 TO 150 300 50 100 TO 250 300
	* column nr TO column nr	* 100 TO 500 400 TO 600	* 50 100 TO 500 600 200 400 TO 600 700
SAVEIMG	# category "category name"	# 5 forest	# 5 forest

3.2 Classification parameterisation

All classifications were based on the same set of training data. Procedural rules were used for initial rule structuring in both methods. Performance of the methods were then iterativley improved by manual changes in rule structures. The maximum likelihood classification was based solely on four TM bands from the April image (3, 4, 5 and 7).

Initial *guide* rules were derived from a set of training data including four bands in the April image (3, 4, 5 and 7), the first component of a principal component analysis from 12 bands of the two TM scenes (excluding band 1, and holding 78 % of the variation from the other 12), one image of LAI (Leaf Area Index) from the June image, LAI difference (i.e. growth) between June and April, and wetness from the April image (cf. McCarthy, 1996). The latter images were used because of their physical interpretability. The result of the initial classification was tested against the training data and visually inspected. Wetlands turned out to be the most problematic category to classify. Thus the DEM was used to produce an image of updrain feeding areas to each cell (Desmet and Govers, 1994). Wetlands were then divided in ombrogenic raised bogs (with no or low updrain feeding areas) and topogenic fens (with membership increasing with updrain feeding area). Problems also occurred both between different vegetation classes and between vegetated and non-vegetated classes (i.e. urban areas). Thus the rules for growth (LAI-difference) were altered to be higher for farmland and deciduous trees and lower for urban areas, grassland and coniferous trees respectively.

4 RESULTS

The expert classifier gave the best result, with a highest kappa index of 0.7521 (table 2). This classification was based on the automatically extracted training data from the first PCA component, the LAI difference and bands 5 and 7 from the April scene. Excluding the two raw bands gave almost the same classification accuracy (0.7506), as did also inclusion of all images. Just using the four April TM bands gave a kappa index 0.74. Manual changes in rule structure in general did not improve classification accuracy. The best result for the maximum likelihood classification using the four TM bands was a kappa index 0.71 (table 3). The result of the expert system classification is also shown in simplified form in fig. 2.

Table 2 Error matrix for the expert classification (rows) against ground truth (columns) (kappa index = 0.75)

	Water	Wetland	Coniferous	Deciduous	Grass land	Crops	Bare fields	Urban	Total
Water	4484	10	0	0	0	0	0	0	4494
Wetland	0	55	116	51	0	0	0	0	222
Coniferous	0	38	3642	23	0	9	0	0	3712
Deciduous	0	112	431	421	9	3	6	130	1112
Grass land	0	3	20	6	438	269	3	1	740
Crops	0	4	0	20	113	574	15	78	804
Bare field	0	2	0	1	28	2	172	5	210
Urban	0	15	13	107	148	762	10	1058	2113
Total	4484	239	4222	589	629	1619	206	1257	13407

Table 3 Error matrix for the maximum likelihood classification (rows) against ground truth (columns) (kappa index = 0.71)

	Water	Wetland	Coniferous	Deciduous	Grass land	Crops	Bare fields	Urban	Total
Water	4484	2	0	0	0	0	0	0	4484
Wetland	0	78	309	100	0	0	0	8	465
Coniferous	0	0	3690	0	0	0	0	0	3362
Deciduous	0	25	129	308	2	0	0	24	458
Grass land	0	0	0	11	564	432	0	2	1009
Crops	0	0	0	24	85	661	39	41	822
Bare field	0	0	0	2	24	0	148	50	224
Urban	0	123	93	144	33	18	19	1132	1532
Total	4484	239	4222	589	629	1619	206	1257	13407

5 DISCUSSION

In fuzzy mode *guide* assigns the membership of a single data point to all spatial output classes. This result can be analysed and displayed, and thus used for further improvements in classification. Transparency and easiness to use has made *guide* a successful tool for learning cognisance in image classification and expert system use (Gumbricht, 1996; Gumbricht and McCarthy, 1996). However, a good classification accuracy demands many iterations, and is rather tedious.

A major problem in this application was that the geometrical registration was to poor. By manual inspection of training and ground truth data it was clear that position errors between images were two to three pixels, and not less than one pixel (as indicated by the RMSE of the geometric transformation). The Mazurian landscape has a very small scale topography, and finding points for geometric transformations is hence difficult. The position problems made the use of expert rules very uncertain in the fragmented terrain of the studied area.

6 CONCLUSION

Knowledge acquisition is the bottle neck of expert system applications (cf. Robinson and Frank, 1987). However compared to advanced classification methods expert classification can be intelligible, and used for hypothesis testing. Important relations between processes and patterns can be inferred and evaluated. A problem is that when using multisource and/or multitemporal images geometrical registration must be very accurate.

Methods to improve knowledge acquisition include co-occurence matrices, discriminant analysis and Bayesian approaches (cf. Argialas and Harlow, 1990; Franklin and Peddle, 1989; Lauver and Whistler, 1993; Dymond and Luckman, 1994), and Fuzzy set and Dempster-Shafer theory of evidence (Srinisavan and Richards, 1990 and 1993). Further improvements in image classification, we feel, also need to consider contextual relationships, and we are presently developing and testing an expert system for such a classification (cf. Gumbricht et al., 1995).

7 REFERENCES

Argialas, D.P. and C.A. Harlow, 1990. Computational image interpretation models: an overview and perspective. Photogrammetric Engineering & Remote Sensing, 56, pp. 871-886.

Civco, D.L., 1993. Artificial neural networks for land-cover classification and mapping. Int. J. Geographical Information Systems, 7, pp. 173-186.

Congalton, R.G., K. Green and J. Teply, 1993. Mapping old growth forests on national forest and park lands in the Pacific Northwest from remotely sensed data. Photogrammetric Engineering & Remote Sensing, 59, pp. 529-535.

Desmet, P.J.J. and G. Govers, 1994. Potentials of a GIS-based, three-dimensional USLE-approach for the identification of critical areas at a catchment scale. Working Paper USLE-1 Laboratory of Experimental Geomorphology, Katholieke Universitet Leuven, 23 pp.

Dreyer, P., 1993. Classification of land use cover using optimized neural nets on SPOT data. Photogrammetric Engineering & Remote Sensing 59, pp. 617-621.

Dymond, J.R. and P.G. Luckman, 1994. Direct induction of compact rule-based classifiers for resource mapping. Int. J. Geographical Information Systems, 8, pp. 357-367.

Eastman, J.R., 1993. IDRISI Version 4.1. Update manual. Clark University, Graduate School of Geography, 209 pp.

Fiorella, M., and W.J. Ripple, 1993. Determining succesional stages of temperate coniferous forests with Landsat satellite data, Photogrammetric Engineering & Remote Sensing, 59, pp. 239-246.

Franklin, S.E. and D.R. Peddle, 1989. Spatial texture for improved class discrimination in complex terrain. Int. J. Remote Sensing, 10, pp. 1437-1443.

Gumbricht, T., 1995. Watershed structure and symmetry with runoff and water quality. In: B. Wiezik (ed), Hydrological processes in the catchment. Cracow University of Technology, Institute of Water Engineering and Water Management, pp. 37-48.

Gumbricht, T., 1996. Application of GIS in training for environmental management. Journal of Environmental management, 46, pp. 17-30.

Gumbricht, T. and J. McCarthy, 1996. Transparent land surface modeling in GIS. In: Proceedings Geoinformatics '96, West Palm Beach, Florida, USA, April 26-28, in press.

Gumbricht, T., C. Mahlander and J. McCarthy, 1995. Rule based and contextual classification of landscape patches and boundaries. In: J.T. Björke (ed), ScanGIS '95 Proceedings, Trondheim June 12-14, pp. 245-255.

Hepner, G.F., T. Logan, N. Rittner and N. Bryant, 1990. Artificial neural network classification using a minimal training set: Comparison to conventional supervised classification. Photogrammetric Engineering & Remote Sensing, 56, pp. 469-473.

Lauver, C.L. and J.L. Whistler, 1993. A hierarchical classification of Landsat TM imagery to identify natural grassland areas and rare species habitat. Photogrammetric Engineering & Remote Sensing 59, pp. 627-634.

Leung, Y., and K.S. Leung, 1993. An intelligent expert system shell for knowledge-based geographical information systems: 1. The tools. Int. J. Geographic Information System 7, pp. 189-199.

McCarthy, J., 1996. Leaf area estimation for hydroclimatological models. Manuscript accepted for Nordic Hydrological Conference 1996.

Middelkoop, H. and L.L.F. Janssen, 1991. Implementation of temporal relationships in knowledge based classification of satellite images. Photogrammetric Engineering & Remote Sensing 57, pp. 937-945.

Ripl, W. and T. Gumbricht, 1996. Integrating landscape structure and clean water production. Presented at Stockholm Water Symposium '95, submitted to Ambio.

Robinson, V.B., and A.U. Frank, 1987. Expert systems for geographical information systems. Photogrammetric Engineering & Remote Sensing, 53, pp. 1435-1441.

Ryan, T.W., P.J. Sementilli, B. Yuen, and B.R. Hunt, 1991. Extraction of shoreline features by neural nets and image processing. Photogrammetric Engineering & Remote Sensing, 57, pp. 947-955.

Skidmore; A.K., P.J. Ryan, W. Dawes, D. Short and E. O'Loughlin, 1991. Use of expert system to map forest soils from a geographical information system. Int. J. Geographical Information Systems, 5, pp. 431-445.

Srinisavan, A. and J.A. Richards, 1990. Knowledge-based techniques for multi-source classification. Int. J. Geographical Information Systems, 4, pp. 505-525.

Srinisavan, A. and J.A. Richards, 1993. Analysis of GIS spatial data using knowledge-based methods. Int. J. Geographic Information Systems, 7, pp. 479-500.

Wang, F., 1994. Towards a natural language user interface: an approach of fuzzy query. Int. J. Geographical information Systems, 8, pp. 143-162.

Wu, J.K., D.S. Cheng, W.T. Wang and D.L. Cai, 1988. Model based remotely sensed imagery interpretation. Int. J. Remote Sensing, 9, pp. 1347-1356.

Worboys, M.F. 1994. Object-oriented approaches to geo-referenced information. Int. J. Geographical Information Systems, 8, pp. 385-399.

Zeff, I and C.J. Merry, 1993. Thematic mapper data for forest resource allocation. Photogrammetric Engineering and Remote Sensing 59, pp. 93-99.