THE USE OF EXPERT SYSTEM AND SUPERVISED RELAXATION TECHNIQUES TO IMPROVE SPOT IMAGE CLASSIFICATION USING SPATIAL CONTEXT

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ABSTRACT

Two methods have been tested in order to improve land use mapping in a post-classification refinement process: supervised relaxation and an expert system. Both methods use multiple sources of information and return satisfactory results. Statistical measurements of texture have been used to provide ancillary information for land use mapping at a super-class level (general classes) in a land cover classification tree. The reasoning model of the supervised relaxation technique is based upon the Bayesian theory. In contrast, the expert system uses the Dempster-Shafer reasoning scheme and allows evidence to be propagated at various levels in the land cover taxonomic hierarchy. The result of this approach may be a mixed-level map product, if the available amount of evidence is insufficient to decide among singleton competing labels. Thus, limitations in the entry-data set for accurate and fine classifications can be defined and resolved. The knowledge base of the expert system contains a set of 40 spatial context rules.

Keywords: Expert Systems, Post-Classification, Supervised Relaxation, Thematic Mapping, Dempster-Shafer Reasoning.

INTRODUCTION

The requirements of the European Commission for the production of agricultural statistics on the main crop types for the European Communities (MARS project) and for automatic land cover map updating (CORINE project) make indispensable the use of high resolution satellite data, because the latter consitutes the only type of data which is usable for repeated assessment of quantitative and qualitative information regarding land use on a large scale. However the use of satellite data in combination with low and medium-level analysis techniques [2] very often gives noisy map-like products which may not be of operational value. In fact, early classification attempts using single date SPOT imagery, provided us with products which were dominated by many residual inaccuracies and class ambiguities. Only after the preprocessing of the satellite data by the Nagao-Matsuyama edge preserving smoothing filter [6], was a statistical accuracy of 65.67% reached. However many thematic inaccuracies remained and these included isolated misclassified pixels scattered throughout homogeneous land use classes and eroded border lines of various object types.

There are many reasons for the difficulty of producing reliable noise-free classifications foremost among which is the adequacy of the training sample and the performance of the clustering algorithm. Furthermore the statistical parametrical models, used in the classification phase, involve ideal approximations to reality (e.g. Gaussian density functions) and therefore make it difficult to put "impure" pixels into unique classes. Another major reason is that we force the matching of statistically separable classes (with respect to their radiometry), to natural classes perceived and mapped by the photo-interpreter. That is we generally aim to achieve in a machine assisted photo-interpretation method all the characteristics of a "human remote sensing system", which applies logical reasoning, takes account of contextual relationships, assesses similarities and disparities among the various objects, perceives and occasionally estimates bio-geophysical parameters using either absolute or subjective measurements [1]. We believe that this 'human' remote sensing procedure can be best simulated by augmenting the raw satellite data with ancillary qualitative and quantitative information relating to the natural environment, developing a methodology for analysing multi-source information, exploring the relevant human scientific, heuristic and common-sense knowledge used in image photo-interpretation, introducing adequate reasoning models into the decision-making process and integrating both data and techniques into an expert system aiming to interpret automatically analog or digital remote-sensing imagery [1]. This holistic approach is sometimes regarded as image understanding. In general the ancillary information can relate to:

1) Geographic context [to help refine pixel/segment classifications on the basis of background geographic parameters: e.g. soil type present; land surface slope, height, aspect; predominant vegetation types expected etc].

2) Spectral properties [particularly to help with the interpretation of multi-temporal spectral signatures for classification purposes].

3) Spatial context [to refine pixel classes on the basis of their neighbourhood/location in an image and to assist in the generalization of a pixel-based product to a more cartographically acceptable structure].

In the present study we have aimed to derive additional sources of land use information and to integrate them into a raster format data base. We have also conducted experiments using the "Supervised Relaxation" and "Expert System" techniques in order to reduce the above inaccuracies in a post-classification process. In the remainder of the paper we shall demonstrate the methods and the results achieved by these approaches.

STRATIFICATION USING TEXTURE

In our experiments with SPOT imagery we have found that texture information has significant potential to discriminate some land cover classes which have overlapping radiometric properties. In order to utilize texture information we have computed various statistics (based on [7]) instead of symbolic or structural descriptions. Co-occurrence matrices were calculated for different "resolution sizes", "displacement vectors" and "orientations" and texture signatures were extracted for the main land cover types. It was found that in view of the spatial resolution of SPOT, the textural appearance of the classes alone may not be used as a means for their identification but that it provides a useful complement to the radiometric data. From the set of texture statistics, it was found that the "variance" feature computed in a 10x10 resolution cell can be used to describe four distinct land use super-classes (level 1 of our taxonomic hierarchy, see fig. 1) with respect to the Swain-Fu distance separability criterion (all the texture calculations were "orientation" invariant). Hence in our work on thematic mapping improvement the classification of the variance layer, is considered as an additional layer of land use information which will assist the relabelling of pixels in a post classification process, according to the contextual relationships present in the image plane.

COMBINED USE OF SPECTRAL TEXTURAL AND CONTEXTUAL CHARACTERISTICS

SUPERVISED RELAXATION

Many different approaches exist for dealing with multisource data analysis and contextual characteristics (e.g statistical data analysis, map algebra, the theory of evidence). In this study we have adopted "Supervised Relaxation labelling"[4]. The method uses a probabilistic updating rule and tries to attain a better consistency among pixel labels with

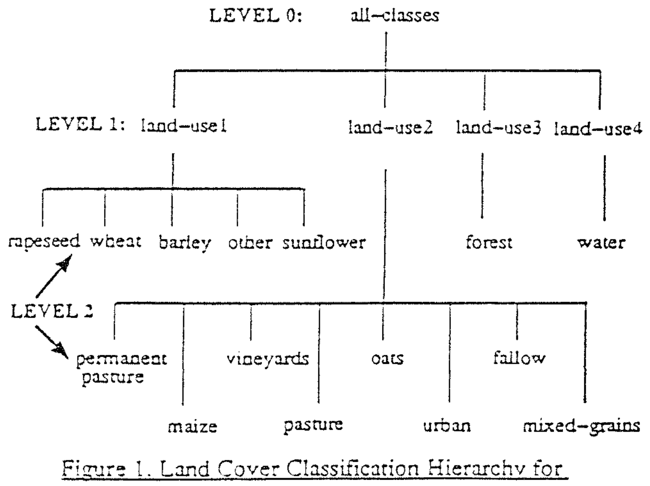


Figure 1. Land Cover Classification Hierarchy for Experiments in Loir–et–Cher

respect to their neighborhoods and to the auxiliary data sources. Dependency among labels is incorporated via compatibility coefficients P_{ij} (W_k, W_l) -where i, j are neighbouring pixels and W_k and W_l are classes. This coefficient indicates the probability of pixel i being of class W_k if pixel j is of class W_l. The estimation of the coefficients is based on a set of likelihoods provided by the use of the following layers of information:-

1) the classification map derived from the 3 channels of SPOT-XS imagery,
2) the probability map associated with the classification in 1 above,
3) the classification map derived from the texture layer
4) the probability map associated with the classification in 2 above.

Our computation of the compatibility coefficients is given by the following procedure:

Step 1: The coefficients vary from place to place on the image plane. So, we define a square window scanning the image, inside which the complete set of $P_{ij}(W_k, W_l)$ coefficients for all the possible pairs (W_k, W_l) will be estimated. W_k, W_l are drawn from the set of labels $[W_1, \ldots, W_m]$. Here "m" denotes the total number of labels in the classification scheme.

Step 2: Select inside the window a random number of pixels. The coefficient calculations are done for each of these.

Step 3: For each selected pixel within the window we choose a sampling strategy -either to compute coefficients with its directly 4-connected neighbours or to compute coefficients within a 5x5 sub-window centred on that pixel.

Step 4: Finally we calculate the compatibility coefficients in the neighbourhood of the selected pixels by the means of the two probability layers and the "supervision" of the texture classification as follows:

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

where R_{i1} and R_{i2} refer to the respective likelihoods of the selected pixel being in class W_k based on the probability data in layers (2) and (4) respectively; and R_{j1} and R_{j2} refer to the likelihoods of the neighbour pixel being in class W_l based on the data in the probability layers (2) and (4) respectively. Thereafter we find the mean value over the total number of selected pixels.

The constant "b" is the so-called degree of supervision; it reflects the confidence of the analyst in the auxiliary data. The value of "b" is chosen heuristically.

In order to evaluate the performance of the algorithm, the classification map in layer 1 above has been updated iteratively (using the relaxation method of [8]) for different values of the parameter "b". The experiment showed that the rate of increase of the classification accuracy is a function of the iteration number and the degree of supervision "b". Furthermore, the choice of the value of "b" is crucial, since it influences the results. In general, a larger value results in a more rapid improvement in the classification accuracy. At the same time the number of required iterations (that is the no. of iterations to maximize the rate of increase) decreases. Overall classification improvement of the order of 10% has been achieved after the third iteration for different values of "b". However, for high values of "b", the thematic accuracy of the map starts to deteriorate because they cause the texture information from probability layer 4 to dominate the post-classification.

USE OF EXPERT SYSTEM IN SATELLITE MAPPING

Handling Uncertainty: Use of Belief Functions- One of the main drawbacks of the reasoning models commonly used in classification approaches is that pixels are forced to take a single class label, even though in some cases the likelihood values commited are not sufficiently different to decide between competing labels. Thus, some method for handling uncertainty is required, in order to avoid class assignments which are only vaguely supported and to assign pixels to class labels which lie in a higher (super-class) level in a classification hierarchy such as fig. 1. A correct super-class is arguably thematically more useful than an incorrect low-level class. It is also desirable to be able to deal with a large body of evidence provided by a set of supplementing data sources (texture, probability layers) and a set of rules encompassing the relevant scientific, heuristic and common-sense knowledge. The numerical reasoning scheme that we have adopted is based on the "belief function" method of the Dempster-Shafer (D-S) theory of evidence. An important feature of the D-S theory is that it provides the means for a mathematical expression of the notions "ignorance" and "uncertainty". These two notions are considered as necessary components of the decision making process of an expert system which we want to translate faithfully the human knowledge.

Spatial Context Rules; the Classification Expert- We are developing an image analysis expert system to enable us to produce in a post-classification process, thematically more useful maps of the Département Loir-et-Cher (France), using the same set of four input layers as in the Supervised Relaxation approach. The system design separates the knowledge required to solve the pixel classification problem from the problem-solving mechanism. This problem-solving mechanism utilizes the Gordon-Shortliffe approximation [5] of the D-S reasoning model, while the knowledge base comprises a set of about 40 rules concerning the spatial context of the pixel as well as a set of data and facts. Data and facts refer to the classification of a 4-connected window which scans the image plane, in both levels of the tree hierarchy. They are variables instantiated to numbers or booleans and return information about the label of the central pixel in the window, the label of its parent class, the location of the parent and child labels in the tree, the number of labels in the 4-connected window that match the classification of the central pixel, the number of pixels in the super-class (parent) level that match the classes (at the bottom level) as parents in the tree, etc. As the input layers (classification and probability maps) are scanned, the values of data and facts relating to the current position of the 4-connected window are stored in a "fact_file", in the form of "Prolog facts" :
[e.g class_supp_by_super_class_lev (Xcoor, Ycoor, Level, Parlevel, True or False, Degreeofsupport)]. Thus, they may be used directly in the expert system which has been developed in the Quintec-Prolog environment. The rules have a condition part which consists of a number of items of data and facts and an action part which commit a certain piece of confirming or disconfirming evidence to a class or super-class. The pieces of evidence are written into an output "evidence_file" in order to be used in a following step by the reasoning model of the system. Typical examples of rules in "Structured English" notation are given in [3]. A modular representation of the rules, has been designed in order to be able to separate various forms of knowledge and to modify or add new rules without it being necessary to recompile the whole system. Rule manipulation (e.g creation, maintenance, firing, access) is done by the use of the "Flex engine predicates" which have been implemented in Prolog as part of the Quintec Prolog-Flex shell. The rules are triggered according to a forward chaining control strategy with a "first come first served" selection algorithm and a "fixed" rule agenda. Fig. 2 shows the main algorithmic steps for an expert system solution to the multi-source post-classification problem. Results from our initial experiments based on Fortran simulations of the expert system method for producing thematic maps of land use in the Department Loir-et-Cher are shown in fig. 3. Overall classification improvement of the order of 10% has been achieved in these experiments.

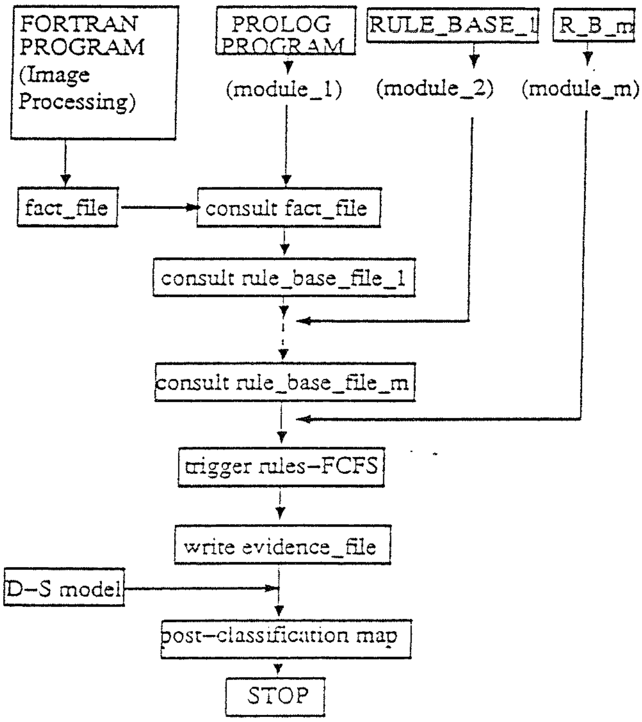
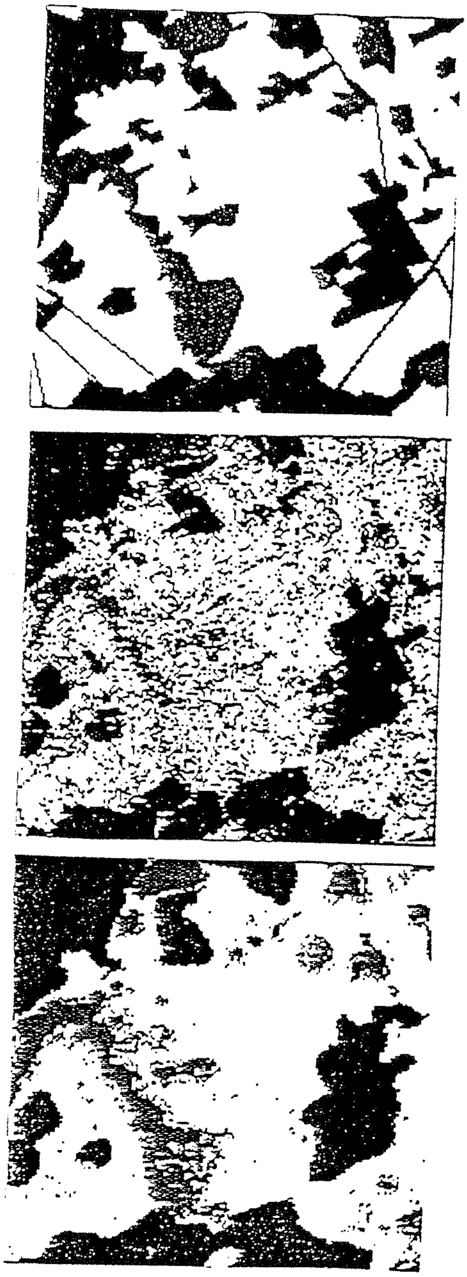


Figure 2. Algorithmic Stages in the Expert System

CONCLUSION

In this paper we have presented a probabilistic (Supervised Relaxation) and evidential (Expert System) approach for thematic mapping, which allow us to combine multiple sources of information in a post-classification procedure. Both methods have provided satisfactory results by improving the initial pixel classifications. Also, they are both computationally efficient, they may deal with numerical and symbolic type data and they can handle uncertainty. However, the expert system application provided us with classification maps of better quality from a thematic point of view since the relaxation method allowed the texture information to dominate the class refinement. Also, the expert system approach does



KEY:
Agricultural (+roads)
Water, lake area
Forest

Figure 3

(The pictures above show the results obtained in the experiments in the Loir-et-Cher region of France. Each image is a 220x220 pixel subscene extracted from the SPOT imagery. The top figure is a photo-interpretation map, the centre the first classification product and the bottom the refined classification product. The figures show only the classification at the super-class level because of the restriction on use of grey-scales for reproduction. The images were classified using the hierarchical scheme described in the text with 15 classes at the bottom level. The two agricultural super-classes have been merged in the figures. Note that the road features are unavoidably removed in the spatial generalisation process.)

not present any limitation in the number of input data-sources. Thus, any new layer of information can be added to the data base, requiring only that a new set of rules accounting for the new input has to be designed [the algorithm foresees a maximum number of 5 levels in the taxonomic hierarchy]. An important characteristic of the expert system solution is that it handles uncertainty more flexibly and produces mixed-level products in cases where there is insufficient evidence to decide between competing singleton classes at the bottom level of the tree hierarchy. In such areas we can deduce that extra information is required in order to resolve the individual classes concerned. At this early stage of the development we feel there are many further extensions to be investigated, such as the addition of spectral signature rules and background geographic rules, the introduction of higher level image pre-processing algorithms (segmentation, boundary detection, segment context instead of pixel context) and the development of a well-designed user interface, before this method becomes of operational use. We hope to experiment further with these ideas in the context of operational experiments.

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