UPSTAIRS as a Framework for Implementing a Geocoded Thematic Database

Helmut Schumaker

Klein + Stekl GmbH

ABSTRACT

UPSTAIRS is a raster image processing system for remotely sensed data. In this paper, a brief overview of the system architecture of UPSTAIRS is given. UPSTAIRS maintains a proprietary data base for images, look-up tables, ground control points, chips and digital elevation models.
An interface to geographical information systems is realized for raster data and is planned for vector data.
In the second part of this paper, the UPSTAIRS function for geometric processing are briefly outlined. Next, the UPSTAIRS subsystem for supervised classification is presented. Conventional (maximum likelihood) as well as non-orthodox classification methods are presented. New classification paradigms such as fuzzy sets and context-sensitive heuristics are discussed. A new approach to multi-temporal classification is presented. Finally, the architecture of geocoded land-use database is proposed. A quasi-automatic procedure for geocode newly acquired data and a classification process based on the fuzzy set paradigm is presented. Integration of new data into the database is discussed.

1. UPSTAIRS

1.1 Introduction

UPSTAIRS (Universal Processing System for Treasuring up and Analyzing Images in Remote Sensing) is a raster image system for processing remotely sensed data (mainly LANDSAT). UPSTAIRS has been developped since 1980 in cooperation with DLR (Deutsche Forschungsanstalt für Luft- und Raumfahrt, Oberpfaffenhofen) and BGR (Bundesanstalt für Geowissenschaften und Rohstoffe, Hannover) and is in operation at several research and university institutes. DLR is the principal user; essential parts of the geocoding software for ERS-1 have been developped there on the basis of UPSTAIRS.
UPSTAIRS was designed as turn-key system. However, users are encouraged to develop their own applications.
UPSTAIRS has been implemented on DEC VAX systems as well as on SUN UNIX workstations.
UPSTAIRS provides to the user a fairly comprehensive set of application programs. Most of the applications are applicable to any raster data independent of the data source; other programs are tailored to LANDSAT SPOT, SPOT or SAR data.

1.2 Database

One of the salient features of UPSTAIRS is its proprietory database which is in fact a complex file system and not comparable to a commercially available product like a relational database. The motivation for providing a database for processing remotely sensed images has been:

- improved consistency of data
- virtually unlimited space for storing image data (no physical limit, but by the sum of all disk space)
- database access routines provide a number of service
- easy realization of distributed data within a network.

The UPSTAIRS database is comprised of several disjoint subsystems. Each subsystem has the same physical, but a distinct logical organization. The database as a whole provides storage and access to the following objects:
layers: rectangles of image raster data; "monospectral image"
images: ordered set of layers; "multispectral image"
lattices: set of a layers in the same hierarchy level; in case of overlapping: precedence is defined; between layers: background grey-value; lattices may be multispectral like images
look-up tables

training areas
class statistics
image control points: reference points associated with image data; pixel coordinates
ground control points (GCP): reference points independent of any particular image; geographic coordinates
chips: small rectangles of image data representing some neighborhood of a GCP
maps: map sheets used for identifying GCPs
digital elevation models: several logical separate databases for digital elevation data
Some of these objects are public, others are privately owned by one or more users.

1.3 Physical Organization

The database consists of up to 255 files. Each file contains only one type of objects, e.g. image data, look-up tables, GCPs, etc. Dependent on the object, the bucket size (record size) is fixed. Each bucket in the database has a unique identifier. Access to data is performed by some kind of demand paging which is implemented in software. For example, when processing an image, the access routines keep the most recently used data in memory and perform necessary updating (write through). The main benefit of this method is that application programs are relieved from the task of optimizing the use of available main memory.

1.4 Logical Organization

Private data comprise image-related data (image data, auxiliary data, image control points, training areas, class statistics) and look-up tables. These data are associated with images which are identified by a name. For each user, a catalog with the currently stored images and look-up tables is held. Public data are ground control points, chips and maps as well as digital elevation models.
The image data are organized as sets of layers which are arrays of any size. Pixel values may be of type byte, halfword, fullword, real, or complex. Layers are identified by a name. Layers may be associated with more than one image with often saves duplicating image data. A valuable design feature is the association of a look-up table with a layer; in this way, pixel values may undergo a translation which is performed when accessing the data. For example, performing a contrast enhancement or density slicing does not require physical copying the image data; instead, the following is done:

1) a new image (output image) is created; this image is void of layers
2) the layers of the input image are also associated with the output image; so, the layer data are stored just once; however, there are two different access paths to the layer data
3) look-up tables are stored with the output layers; thus, when accessing the layer data via the output image, a translation of the pixel values is performed. The original pixel values are preserved and are retrived when accessed via the input image.

1.5 Access Methods

Some of the recurrent functions in image processing are encorporated in the database access services. These functions are performed when writing to or reading from the database:
- data conversion (e.g. byte to halfword)
- table look-up
- linear mapping of gray-values
- clipping of gray-values
- calculating a histogram of gray-values
- resampling (nearest neighbor, bilinear, cubic convolution)

1.6 Interfaces

UPSTAIRS has only limited capabilities for processor vector data. It was never designed for performing applications which are based on vector processing operations. UPSTAIRS can be understood as a complementary subsystem for geographic information systems. Whereas an interface for exchanging vector data is only planned for, UPSTAIRS supports a number of common raster image formats for importing and exporting image data (e.g. SUN raster format, ERDAS).

2. GEOMETRICAL PROCESSING

2.1 Database

The database provides services for storing and accessing public data for geometric processing:
- map sheets
- ground control points (GCP) and chips
- digital elevation model (DEM)

Map sheets

The purpose of defining map sheets in the database is to impose some hierarchical order on some of the GCPs. They are used when digitizing GCPs.

Ground Control Points and Chips

GCP coordinates are stored in longitude and latitude. When accessing GCPs, a transformation of the coordinates to UTM or Grauss-Kruger may be requested. Optionally, one or more chips may be stored with each GCP [Schreier, Kosmann and Schumacher, 1988].

Digital Elevation Model

Many DEMs may be held in the database concurrently. Each DEM is based on geographic coordinates and may cover the whole earth. Data may be stored in one of some 20 different resolutions between 1 second and 1.5 degrees. Within a single DEM, any combination of these resolutions is possible; however, one data value only may be assigned to a location. The elevation values are of type integer (16 bits) [Schreier, Knoepfle, Craubner and Schumacher, 1990].
Data are organized as raster data; because of the implementation as a tree, fast access to any single location or to any rectangle is possible.

2.2 Methods

Geometric correction algorithms for image raster data in UPSTAIRS are of type ruber sheeting: polyonomial mappings to reference images as well as to some map system (GCPs). For LANDSAT TM raw data, a correction process based on a system model and ephemeris data has been developped.
A full-scale application based on the UPSTAIRS database services (GCPs and chips as well as DEMs) is the GEOS system, developped by DLR, IPI (Institut fur Photogrammetrie und Ingenieurvermessungen, Hannover) and two other university institutes. GEOS is an operational system for the D-PAF SAR geocoding [Schreier, Kosmann and Roth, 1990].

3. CLASSIFICATION

3.1 Introduction

The classification subsystem in UPSTAIRS provides techniques and methods for supervised classification. The basic classification method in UPSTAIRS is the maximum likelihood method as this method is the classical method and has a sound theoretical foundation [Richards, 1986]. However, this method - like most conventional classification methods - has a number of drawbacks. Some of the problems with this method are of technical nature:

- the prerequisite of normal distribution of the features is not always guaranteed in practice
- ill-conditioned covariance matrices may be encountered

Other drawbacks are of a more fundamental nature. So, the model underlying the maximum likelihood method is a probalistic one: it is not well suited for coping with vague and imprecise information like the class coverage of small rectangular areas (pixels). Therefore, in UPSTAIRS this method has been generalized and developped further:

- to circumvent technical problems, a robust implementation of the maximum likelihood method is available;
- in order to facilitate the process of feature selection, a generalization of the method (which is no longer maximum likelihood in a strict sense) is provided;
- as an alternative, a fuzzy classification concept has been developped which is more appropriate to deal with the vagueness of pixel classification;
- based on this fuzzy concept, a tentative, partial solution to the problem of detecting and resolving mixed pixels is provided;
- a new approach to multi-temporal classification is offered;
- an effective contest-sensitive fuzzy reclassification method is provided.

All of these methods are discussed at length in [Schumacher, 1991].

3.2 Data

Data for classification are comprised of:

- training areas
- class statistics

The user may choose any number of subsets of training areas for calculating class statistics. The extremes are:

- all training areas are combined
- each training area is considered as a separate subclass

So, some emphasis has been put on developping a robust classification method which can handle this situation.

3.3 Standard Methods

Over time, several different implementations have been made available in UPSTAIRS. In my view, the best method which incidentally is the standard implementation in UPSTAIRS today, is what I call the SVD method. SVD stands for singular value decomposition. Instead of calculating the Mahalanobis distances for all classes in a common feature space, these distances are calculated in class-specific spaces of the same dimension. For each class, a principal components analysis is performed. The eigenvectors of this analysis form the coordinates of the class- specific feature space (transformed features). The distances measured in the transformed feature spaces can be compared in the same way as the original distances and result in identical classification results.
Although this seems a bit complicated in the first place, there are several advantages of this method:

- as a mattera fact, compared to the conventional implementation, this method can be expected to be faster by half an order of magnitude;
- in practice, covariance matrices easily may be ill- conditioned; with the SVD method, singularities of the covariance matrices are detected. The resolution of this problem is the reduction of the dimension n of the feature space: for $m < n$ main features the Mahalanobis distances are calculated, for the remaining residual features $r = n - m$ features a threshold method is used (essentially, for the residual features, the hyper-ellipsoid is approximated by a hyper-parallel-epiped).
- an analysis of the eigenvalues of the covariance matrices reveals that in practice most of the information that can be used for discriminating among the classes is contained in only a few of the transformed features. That is, there is good reason to discard some of the transformed features corresponding to small eigenvalues. Therefore, a reduction of the dimension of the feature space is of intrinsic value even if there is no need for numerical reasons.

This implementation has the potential for classifyng remotely sensed data of high feature dimension, e.g. data of imaging spectrometers. Even for LANDSAT data, there should be no need any more to select a fixed subset of the available features. It is perfectly reasonable to execute this algorithm with all available original features; this method adjusts to any difficulties automatically and gets the most information out of the features.

3.4 Fuzzy Classification

A very important concept for improving conventional classification methods is the paradigms of fuzzy sets [Zadeh, 1977]. In the literature, a number of authors propose classification methods using the fuzzy set concept (e.g. [Wang, 1990]).
The limitation of the classical approach to pixel classification is obvious. A pixel assigned to exactly one class (or is left unassigned); however, in reality, a pixel might be a mixture of several classes. The concept of fuzzy sets allows for the distinction of uncertainty if we do not have enough information; however, if additional features were available, we possibly could reduce the uncertainty of an assignment.
On the other hand, in case a pixel does not fit exactly to one of a set of given classes, an assignment can only be vague: additional information cannot resolve the inherent dilemma.
Whereas uncertainty may be handled by the classical concept of probability, vagueness may be taken care of by memberships. As for probabilities, a memebership is a real number in the range 0 to 1. However, as opposed to probabilities, memberships do not have to be normalized: the memberships of a pixel to a number of classes do not have to add up to 1. This is of great advantage in later steps of the classification and for analysis purposes: the closeness of fit to each class is preserved.

So, the first application of fuzzy sets in UPSTAIRS is a generalization of the maximum likelihood method where the resultant classification of a pixel is not a single class assignment, but a vector of class memberships (in reality, only the three classes with greatest memberships are stored). In order to determine memberships, the resultant Mahalanobis distances have to be transformed into memberships. There is no unique way for doing this; in UPSTAIRS, we have chosen a somewhat arbitrary transformation. As classes are no longer ordered by likelihood, but by membership instead, this is no longer a maximum likelhood classifier. The advantage of this fuzzy method is in additional membership information which may be used in later analysis steps.

However the benefits of the fuzzy concepts are greater by far. With memberships we do have a means for normalizing distances in feature space, i.e. we are able to compare closeness of a pixel to any class by comparing memberships no matter how we estimate the memberships. The practical consequences are:

- the fuzzy classifier presented above may be generalized further such that the Mahalanobis distances are calculated in feature spaces of different dimensions. When comparing likelihood (probability distributions), the same dimension is required; therefore, the SVD-classifier presented above required the same dimension m of

main features for all classes. A fuzzy version of the SVD-classifier allows different numbers of main features for the various classes.
- different classifiers may be combined in a single classification run. For example, a box classifier (essentially a parallel-epided classified with an internal metric for assigning memberships) may be used for some classes, a Mahalanobis classifier for others.

3.5 Class-Specific Features

Technically, it is now possible to design fuzzy classifiers which are based on a different number of features. In my view, this is a useful and potentially powerful concept.
For the SVD-classifier, it is no longer necessary to require the same number of main features and residual features; there may be a class-specific division of m_i main features and r_i residual features such that $m_i + r_i = n$. As a further generalization, the need to require the same set of n original features can be abandonned. Thus, any n_i original features should be allowed.
This alleviates a problem anyone is confronted with when applying the maximum likelihood classifier in practice: very often, it is difficult to fulfill the theroetical requirements of the maximum likelihood method: multivariate normal distribution of the features in cases with a large number of features or small training areas, it is difficult to get a normal distribution in all features. Thus, it can be argued, it is better to discard features for which the requirement of normality is not fulfilled than to use these features getting poor results. With the proposed concept, it is possible to select features on a per class basis.
Of course, as soon as we do have different feature spaces which, in the extreme, actually may be disjoint, we may loose some power for discriminating among the classes. So, there is a trade-off between using too many features of possibly poor statistical quality and too few features losing discriminating power. This trade-off should be solved by supervision of the user.

3.6 Mixed Pixels

Mixed pixels are a phenomenon difficult to cope with and particularly frequent in scenes acquired by satellites. With fuzzy classification, a tentative, partial solution can be tried to come up with. The solution consist of two steps to be excuted after completion of the per-pixel fuzzy classification:
1) detection of possible mixed pixels
2) resolution of apparent mixed pixels

Detection

The first task is to find a subset of pixels which possibly could be pixels mixed of two classes:

- pixel with low (or zero) membership and at least two neighborhood pixels with high membership in two different classes;
- isolated pixels: all neighbors are assigned at least two different classes;
- all pixels which are located on the border of two class segments; these pixels may be found by appling rules such as "select pixel if in the neighborhood there are only two different classes assigned with a more or less high membership and with a count of minimum 3 and maximum 5".

The reason for requesting at least two classes in the 3x3-neighborhood is that we need some hint about classes contributing to the pixel. The information "possibly mixed pixel" without possible candidate classes is of no value.

Resolution of Mixed Pixels

The basic idea for resolving a mixed pixel is to examine the location of that pixel in the feature space relative to the location of the cluster centers of the candidate classes.
Technically, this can be done as follows:

- besides the pure candidate classes, a number of mixtures of both classes are constructed as additional (synthetic) classes, the statistics of which can be calculated from the statistics of the two candidate classes;
- for the pixel in question, from all synthetic mixed classes the maximum membership is determined;
- the maximum membership thus obtained is compared to the membership of the original pixel classification; if the membership is greater, the pixel is marked as a mixed pixel; the labels of the mixed pixel are the two candidate classes; the location of the assigned synthetic mixed class in the feature space is an indication for the relative area coverage of the mixed pixel.

3.7 Context-sensitive Re-classification

When remotely sensed data is classified on a per-pixel basis only, a great deal of information is ignored. The surrounding of a pixel may contribute in removing some uncertainty about the correct class. A traditional approach to integrating context information in the classification process is based on probabilistic relaxation methods [Hummel and Zucker, 1983]. The main problems with these methods are its instability and the fact that probabilities give no good estimate for the closeness of pixels with its respective classes.

In UPSTAIRS, a completely different approach was tried, based on a fuzzy per-pixel pre-classification. The basic idea is to view spectral and context information as two separate sources of information. Both have to be combined somehow in order to get a final conclusion. This resolution process is contingent on certain class characteristics and on the entropy in the vicinity of the pixel in question.

Technically, this re-classification method starts with the fuzzy classification map obtained by a fuzzy pre-classifcation. For each pixel, the spectral memberships are given as the result of this per-pixel classification. The context information is estimated on the basis of this spectral memberships in the neighborhood of the pixel. After combining both memberships for each class, the resultant memberships are taken as the preliminary classification map. In a next iteration, the same process starts with these updated results instead of the original spectral memberships. After very few iterations, the process can be stopped.

In figure 1 the basic situation is shown.

If spectral and contextual membership are highly correlated, deciding on the resultant membership is easy. Otherwise, resolution of the situation depends on several factors.

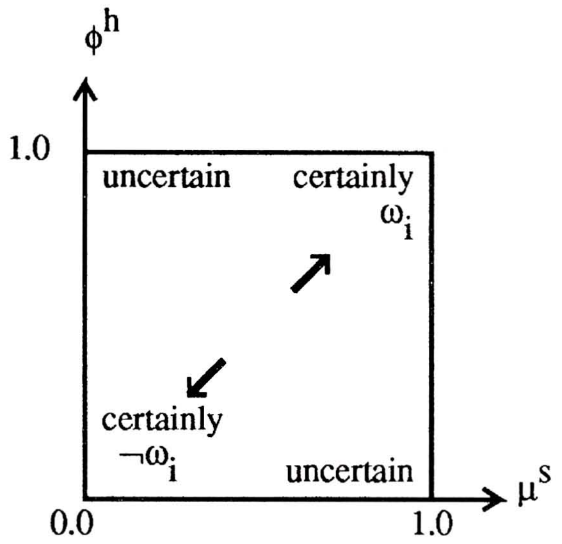

Fig. 1 - Spectral Information μ^s versus Context ϕ^h.

As a first example, consider a non homogeneous class usually covering very small segments. Then there should not be expected too much information from analyzingthe neighborhood of such a pixel. Next, consider a homogeneous class normaly covering large areas. In this case, the degree of coverage of the neighborhood with the same class should influence the class membership. However, this is only true if the neighborhood is of low entropy; if the class coverage of the vicinity of the pixel in question is chaotic, no information can be derived from the context analysis.

Besides the homogeneity of a class, two other global characteristics of classes can be used:

- the degree of co-occurence of all pairs of classes (this criterion is in fact the rationale behind the probabilistic relaxation methods, too);
- the distribution of a class within a scene; if pixels of the same class are within the same region of the scene, the likelihood for a class instance is slightly improved.

It turns out that the effectiveness of the three criteria is in the order

1) homogeneity
2) co-occurrence
3) global distribution

So, in order to find a resultant membership in the general case, the following parameters have to be estimated:

- a global measure for the homogeneity and a global distribution of all classes as well as estimates for the degree of co- occurrence for all pairs of classes;
- a local measure in the 3x3-neighborhood for homogeneity and co-occurrence;
- a measure for the applicability of any context criterion for the pixel in question based on the local entropy.

The global measures are estimated on the basis of the preclassification results. For details on how these measures are estimated and on the entire re-classification process I want to refer to [Schumacher, 1991].

This method has been quantitatively tested with a number of synthetic scenes. In all cases, there was a significant improvement over the results of the preclassification; the error rate could be expected to be reduced by half. It was also shown, that the results using this fuzzy re-classification method can be expected to be much better than results obtained by using probabilistic relaxation methods.

3.8 Multi-temporal Classification

An approach of considerable practical significance is the classification of geometrically congruent scenes of different dates or different sensors: multi-temporal classification. There are at least two different concepts for performing multi-temporal classifications:

- the *stacked approach*: all features are combined to one feature set which is taken as an input for some classification method. This disadvantage is that this is not useful approach if this process has to be repeated over time; also this stacked approach requires valid data for all scenes (e.g. clouds in any one scene preclude classifying those pixels)
- some sequential classification process where the former classification results are incorporated somehow in the classification process of later scenes (e.g. as a-priori probabilities) [Swain, 1978]. The disadvantage of these methods is missing simmetry: later classifications do have more influence on the results than former ones.

The outlined fuzzy classification methods lead to a new approach to multitemporal classification which is symmetrical and applicable to as many scenes as required. In addition, it is possible to control the influence of the various scenes by assigning weights.
The principle is to classify all geometrically congruent scenes separately and combining the fuzzy classification results by performing a fuzzy union: basically, for each pixel and each class, the maximum of memberships is taken.

In [Schumacher, 1991] I suggest to use a slightly different implementation of the fuzzy union. As a matter of fact, for the implementation of fuzzy set operations, at least half a dozen of different function families have been proposed [Klir and Folger, 1988]. The generalized fuzzy union in [Schumacher, 1991] allows for introducing weights in the various operands of the union operator, thus enabling giving weights to the different scenes on a per-class basis.

4. THEMATIC DATABASE

4.1 Introduction

Having presented the tools available for geometrically processing and classifying remotely sensed data in UPSTAIRS, I will propose now an implementation of a geocoded thematic database, i.e. a database for the purpose of maintaining and processing land-use information. The utility of such a database for a GIS is obvious.
In the late seventies, the feasibility of such a database had been studied in a project at DLR at Oberpfaffennhofen [BMBau, 1979], sponsored by the German "Bundesministerium fur raumordnung, Bauwesen und Stadtebau" (Ministery for Urban and Rural Development). The aim of this project was to demonstrate the feasibility of implementing a system capable of

- answering queries about the acreage of various land-use classes within a region (e.g. a municipality);
- producing maps presenting the land use classes within a region.

So, there were two kinds of information to be acquired and stored:
- borders of areas of interest (e.g. municipalites, counties, etc.);
- classification maps (more precise: for each area cell (pixel), assignment to exactly one of a pre-specified set of land-use classes)

Of course, for both types of data a common coordinate system and a fixel resolution had to be chosen. The source for the classification map was to be LANDSAT MSS data, the periodical acquisition of which was to led to a continuing actualization of the classification map. The result of that study was not very encouraging; essentially, pixels falsely classified were too numerous.
Today, an approach for implementing such a land-use database should be much more promising:
1) the quality of the source data is better (e.g. TM, SPOT);
2) the classification methods available today are much more powerful;
3) the paradigm of fuzzy sets provides the means for a more realistic knowledge presentation and processing at the stored land-use information.

In this section, I will
1) discuss some of the inherent and the methodical problems to be solved;
2) propose an architecture for the database;
3) present quasi-automatic procedures for geocoding and classifying source data;
4) discuss methods for integrating newly acquired data into the database.

4.2 Some Problems and Parameters

Functionally, we have to answer at least three different questions:
1) how is the knowledge about the land-use to be characterized and stored?
2) how is the knowledge to be acquired and integrated?
3) how is the knowledge to be accessed and presented?
We are confronted with different inherent problems as a direct result of discretization:
- different land-use over space (mixed pixels)
- different land-use over time (e.g. change in agricultural areas, variation in borders of water bodies)

- imprecise, ambiguous assignments of pixels because of limited numbers and idealization of land-use classes
- difficulty to decide whether a change in land-use is permanent (e.g. forest to street) or temporary (e.g. change in water level of a lake); both cases should be treated differently in the database

Furthermore, methodical problems have to be solved:
- geometric correction of newly acquired source data (requesting sub-pixel accuracy)
- automatic classification of newly acquired source data
- integration of classified data and resolution of conflicts between stored data (historical) and new data (actual); one difficluty here is to judge the confidence in the correctness of the classification of the newly acquired data versus the historical weight of the stored data.

For implementing a land-use database, a number of parameters have to be decided on :
- map system
- resolution
- a fixed set of land-use classes

In my view, it clear that the paradigm of fuzzy sets is of great advantage for the implementation of a land-use database. Assigning mamberships to classes for each pixel instead of requiring a unique class assignment alleviates some of the problem stated above. The advantage of using fuzzy sets is not only that this is more adequate for expressing assignment to land-use classes, it also enables the use of the advanced classification methods presented above. Also, fuzzy sets do not only hels in expressing vagueness; storing memberships to classes keeps a lot more information about the classified pixel which helps in integrating new classified data and in processing stored information.

4.3 Architecture of a Land-Use Database

The first main decision to be made when designing a geoceded database, is choosing a map system and a resolution (pixel size). Two map systems are obviously suitable:
1) UTM (or Gauss-Kruger)
2) geographic (longitude/latitude)

As opposed to the DEM database in UPSTAIRS, a land-use database can be expected to cover only a relatively small area of interest (say, within one UTM zone). Therefore, UTM should be the appropriate map system. The disadvantage of geographic coordinates obviously is that the area size pixels do vary with the latitude; therefore, to obtain any area statistics, each pixel within an area has to be weighted by a factor which is a function of the latitude. Independent of the chosen map system, the implementation within UPSTAIRS would be analoguous to the implementation of the DEM database. However, as opposed to the DEM database (where there are several hierarchy levels of different resolution), for a land-use database a unique resolution could be chosen.
Another important parameter of the database layout is the amount of information to be stored with each pixel. For the thematic information, I suggest to store up to three classes with the corresponding membership, resulting in 6 bytes per pixel. If mixed pixels are to be considered, another byte per class is required, thus resulting in 9 bytes per pixel.
The original source data should probably be stored in a separate geocoded source database where each scene is stored as an entity. Holding source data in the thematic database as additional layers, this essentially would require the mosaicking of overlapping geoceded scenes. However, as mosaicking results in a severe radiometric distortion, this should not be a feasible option for an operational system.
In the pilot project mentioned above [BMBau, 1979], the thematic data were not stored as raster data in a straightforward manner, but as quadtrees. Quadtrees are very efficient for performing Boolean operations as e.g. determining the set of pixels of a certain land-use class within a specific region. However, in that former project at most one class was assigned to each pixel which resulted in a vast reduction of redundance in the databse (i.e. a quadtree was also an efficient method to store the information). With our approach using fuzzy sets, I cannot see how the quadtree method should be superior to the straight raster method suggested above.

4.4 Quasi-Automatic Geometric Processing

An operational system to produce geocoded SAR data has been implemented in the GEOS system which is to process ERS-1 data at the German D-PAF [Schreier, Kosmann and Roth, 1990]. The GEOS system relies on the UPSTAIRS subsystems for ground control points, chips and digital elevation models. Since the proposed thematic database is primarily to be based on LANDSAT and SPOT data, an operational geocoding system for optical sensor data would have to be developped.
Such a subsystem could be outlined as follows:
1) Approximate geometric correction: a mapping from the geocoded coordinate system into the new scene is determined. This could be achieved by means of a

geometric model of the sensor/platform system and ephemeris data (using possibly a few tie points).

2) An equi-distant grid is chosen for the area of the geocoded scene. For each grid point, a chip (search sea) of some fixed size (later to be used for a correlation process) is resampled from the new scene data, using the mapping found in the step 1.
3) For each grid point, a best relative shift between the search area and some geocoded data is estimated by means of some correlation process.
   This correlation should provide - in addition to shifts in two directions - some measure for the degree of confidence in the correctness of these shifts (e.g. a high correlation coefficinet will lead to a high confidence).
4) having an estimate of a shift in all grid points, an approximation algorithms is applied for shifts in x and y separately. This approximation algorithms is a generalization of a method suggested by Grimson [Grimson, 1981], including weights for the disparities in the grid points (zero confidence implies zero cost as no null value is available) [Schumacher, 1991]. The result of this step is a mapping in x and y in all discrete grid points (shifts are in sub-pixel size range).
5) The mappingof step 1 is to be combined with the deviations in the grid points (step 4). Thus, we do have a mapping from the geocoded area back into the new scene for all grid points.
6) The resampling of the new scene to the geocoded system is performed.

The prerequisite for this process is that at least one geocoded scene of the same area is available (i.e. we are talking about integrating new scenes). If more than one geocoded scene is available, the correlation process could be performed with any of these data (e.g. taking the one with the most radiometric similarity).

4.5 Automatic Classification

As a natural consequence of the fixed number of land-use classes, classification of new scenes should be supervised which requires some classifier training. The conventional approach of interactively defining training areas is certainly not feasible. The next idea is, to define training areas once and store these in a database, comparable to chips in the GCP database. The problem with this approach is that training areas defined in a single scene may not be optimal in another scene. For example, a piece of forest might be homogenous in the scene used for defining a training area. In another scene dating from a different season, this piece of forest might actually be divided into two spectrally different segments which will result in a bimodal histogram. Other difficulties might arise from situations where the covariance matrices for some of the subclasses become singular.

Another approach which completely transcends from discrete training areas, is to use entire classification maps of geometrically congruent scenes for calculating the class statistics. This has been proposed elsewhere in the literature in the context of crisp classification [Quiel, 1986] as well as fuzzy classification [Wang, 1990]. Using fuzzy classification maps, this method employs *fuzzy statistics*: pixel assigned to a class are not counted as 1, instead the count is a function of the membership. So, in order to get the class statistics for a supervised classification, the source data of a newly acquired scene are processed with the valid fuzzy classification map; which is stored in the database.

Certainly, these fuzzy class statistics are not as precise as those that could be obtained by interactively defining training areas. Therefore, I suggest an iterative classification process. As a first step after having calculated the fuzzy class statistics, a first fuzzy classification should be performed. The result of this classification, a first fuzzy classification map, should be used for a kind of automatic plausibility step. For this purpose, a fuzzy intersection of the resultant classification map and the contents of the database should be performed. (A fuzzy intersection may be defined as taking the minimum of the memberships of corresponding classes; however a multitude of different, more general functions may be used [Klir and Folger, 1988] [Schumacher, 1991]). In a second calculation of the fuzzy class statistics, the resultant classification map of this intersection process is used (instead of the database contents).

The reasoning behind performing this intersection step is as follows. As an example, we may think of the water surface of a lake which varies over time.

- Suppose, the real surface as presented in the new scene is smaller than nominal. In this case, the fuzzy statistics is distorted by pixel from the surroundings of the lake. The degree of this distortion depends on the relative size of the difference between real and nominal size of the water area.

Two possibilities arise:

1) the difference is small, so the distortion may be such that the resulting statistics are still unimodal, however with somewhat different means and covariances. Some of the real water surface is classified more or less correctly, with a possibly large number of water pixels either unclassified or assigned to a false class. Performing the intersection with the nominal water surface, we obtain only correct water pixels, which will build the basis for the second fuzzy statistics.

2) the difference is large, so the statistics may become multi-modal. Here, things are a bit more complicated. Here the problem will be that not only the difference area between real and nominal water surface will be classified as water; this may lead to misclassification outside the nominal lake, too. The solution must be searched for in some kind of heuristic reasoning: in case of multi-modal distributions, the resulting sets of classified pixels has to be analyzed for each subclass separately. For each subclass, the degree of correlation between the nominal class area and the resultant area of this subclass should be determined. For correctly classified water pixels, almost all of these should be located within the nominal water area. For falsely classified pixels, a more or less high percentage of these can be expected to be located (otherwise we do not have a problem as almost all classified pixels are within the nominal area).

- Now suppose, the real surface as presented in the new scene is larger than nominal. In this case, the fuzzy statistics is based solely on the real water pixels. Therefore, the water pixels in the new scene should be correctly identified as such.

Classification Method

The requirements for a classification method are:
- the classification method must produce a fuzzy classification map;
- the classification method must be detected and corrected (by discarding some features);
- as a consequence of this, the algorithm must be able to operate in feature spaces of different dimension which requires a normalization of distances measures.

These functional requirements are fulfilled by the fuzzy classification methods in UPSTAIRS. As these methods allow for a variable number of features for individual classes, I suggest to take advantage of this fact: it is probably a good idea to select for each class a fixed set of features from the original spectral channels, ratios, etc.

After the iterated classifications, two steps should follow:
- detection and resolution of mixed pixels;
- a context-sensitive re-classification; the estimation of the fuzzy measures used in this algorithm could be learned from the series of classification performed so far, not from the actual scene alone.

Both steps should hopefully improve the quality of the classification results of the new scene before these results are integrated in the database.

Overview

An overview of the complete automatic classification process is given in figure 2. The last step, the integration process, is discussed briefly in the next section.

4.6 Integration of Newly Acquired Data

The integration of the new data in the database is a difficult process. The inherent problem is that
1) the nominal (stored) classification data have intrinsic weight because these data rely in general upon a more or less long sequence of classifications, so misclassification should not be of much importance;
2) the real (new) classification data are the most recent data, so differences to the nominal data might result from changes in ground truth; however, as the new data have been automatically classified, differences might in fact be mis-classifications.

If we go back for a moment to the conventional approach to a land-use database where we do not have a degree of confidence associated with each class assignment, the only practical solution probably would be to give precedence to the new data over the stored once, i.e. the new classification just supersede the old ones.
Within this fuzzy framework, we certainly can do better. Essentially, there are two approaches: a purely technical one and a method based on rules.

Technical Approach

A solution which immediately comes to mind, is to perform a fuzzy union of the stored data and the new data. In this way, in the resultant classification map for each class and each pixel the maximum of both degree of memberships is taken. Again, fuzzy union may be implemented somewhat differently [Klir and Folger, 1988] [Schumacher, 1991], allowing for class-specific weight assigned to the different operands (memberships).

This method has two short-comings:
- memberships of the stored classification map are continually increasing towards 1 and never decrease
- in case there is a real change in landuse, this should be reflected in the classification map by setting the former class membership to 0.

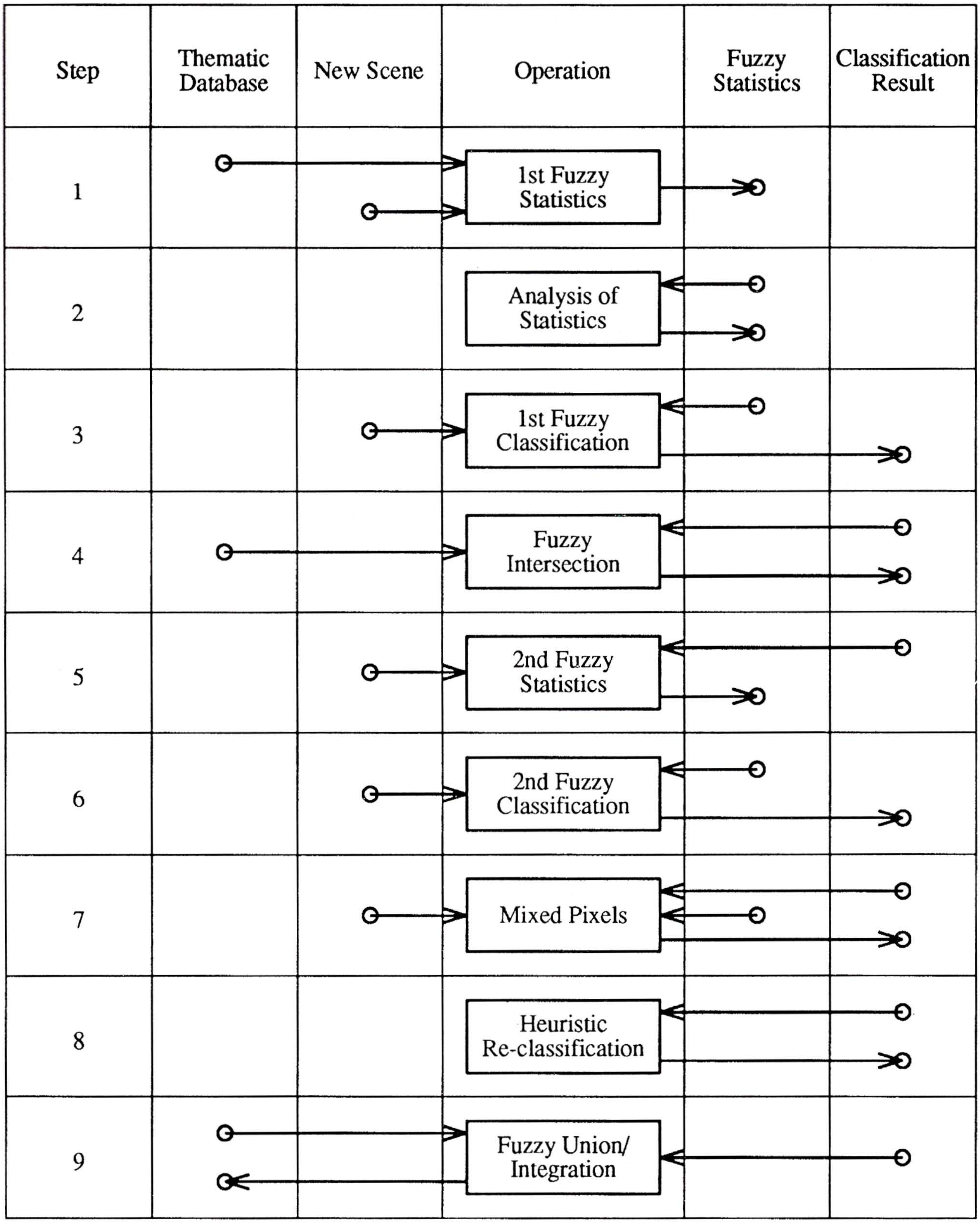

Fig. 2 - Automatic classification for updating thematic database.

Set of Rules

An improvement of the integration process should be obtained by applying a set of rules for resolving non-compatible class assignments. An example of such a rule could be. If the old data is assigned one of the classes [agricultural, forest, ...] with high membership and the new data is assigned one of the classes [street, residential areas, ...] with high membership, assign the new class and discard the old one.
So, the integration of this classified data should be managed by some kind of expert system. The only data the expert system has access to, is a vector of memberships to a fixed set of classes for the data stored in the database (nominal, historical data) and for new, more recent data. The reasoning may, of course, involve arbitrary neighborhoods of a pixel.

SUMMARY AND CONCLUSION

The architecture of a thematic database built upon the tools and methods available in UPSTAIRS was proposed. It was suggested to perform the geometrical process of matching newly acquired scenes to geocoded data by estimating vectors of displacement in a large number of equi-distant grid points. The correlation process to be applied should give - in addition to the displacements - a measure of confidence in the accuracy and authenticity of the homologous points. This measure of confidence can be translated into a coefficient of a cost function for an approximation algorithm suggested by Grimson [Grimson, 1981]. This approximation process gives the best estimate of the displacements in the grid points resolving a trade-off between the original estimates (null values of displacement) and the "smoothness" of the global solution which is a parameter of the process.
For the classification of newly acquired scenes on a continuous basis, an automatic process is suggested. The supervised classification methods in UPSTAIRS provide a strong foundation for such a system. A method for training the classifiers on the basis of fuzzy statistics based on former classification results rather than individual training areas is proposed. The salient features of the classification subsystem are:

- fast, robust implementation of the maximum likelihood method, also applicable in case of a large number of features
- fuzzy set paradigm for expressing vagueness of classifications
- different sets of features on a per-class basis are possible
- different types of classifiers may be combined within a single classification run
- partial solution to the detection and resolution of mixed pixels
- new approach to multi-temporal classifications by combining separate classification results by means of fuzzy set operations
- new context-sensitive fuzzy reclassification method where context information is estimated on the basis of a fuzzy per- pixel classification, considers spectral and context memberships as two sources of information, and tries to combine both sources to one final classification result.

All classification methods in upstairs are operating on a per-pixel basis or are based on the smallest neighborhood context only. For an operational thematic database, it might well turn out that such a low-level approach is not sufficient. In particular, no ancillary information is integrated in the classification process. Certainly, there are very difficult problem areas (like cyclical changes in agricultural land-use) which probably require a complementary knowledge-based approach [Middelkoop and Janssen, 1991]. Also, in order to resolve discrepancies between old (historical) and new (actual) land-use classification, the fuzzy set paradigm is of great help; however, a considerable improvement in this decision process (changes in ground truth versus mis-classifications) can be expected by applying a set of rules for integrating new classification results in the database. So, a logical consequence of this would be the development of an expert system which is built on top of this low-level classification system suggested.

REFERENCES

BMBau. Auswertung von Satellitenaufnahmen zur Gewinnung von Flächennutzungsdaten. Technical report, Bundesministerium für Raumordnung, Bauwesen und Städtebau, 1979.

W.E.L. Grimson. From Images to Surfaces - A Computational Study of the Human Early Visual System. MIT Press, 1981.

Robert A. Hummel and Steven W. Zucker. On the Foundations of Relaxations Labeling Processes. IEEE Transactions on Pattern Analysis and Machine Intelligence, 5(3): 267-287, May 1983.

George J. Klir and Tina A. Folger. Fuzzy Sets, Uncertainty, and Information. Prentice Hall, 1988.

Hans Middelkoop and Lucas L.F. Janssen. Implementation of Temporal Relationships in Knowledge-Based Classification of Satellite Images. Photogrammetric Engineering & Remote Sensing, 57(6): 937-945, 1991.

Friedrich Quiel. Landnutzungskartierung mit LANDSAT- Daten. Technical Report 17, Bundesforschungsanstalt für Landeskunde und Raumordnung, 1986.

J.A. Richards. Remote Sensing Digital Image Analysis. Springer-Verlag, 1986.

Helmut Schumacher. Untersuchungen zur überwachten Klassifikation von Fernerkundungsaufnahmen. Technical Report 169, Fachrichtung Vermessungswesen der Universität Hannover, 1991.

G. Schreier, W. Knoepfle, H. Craubner and H. Schumacher. A Large Scale Data Base for Digital Elevation Models. In ISPRS Commission IV Tsukuba, 1990.

G. Schreier, D. Kosmann and A. Roth. Design Aspect and Implementation of a System for Geocoding Satellite SAR Images. ISPRS Journal of Photogrammetry and Remote Sensing, 45: 1-16, 1990.

G. Schreier, D. Kosmann and H. Schumaker. Data Bases for Operational SAR geocoding Systems. In ISPRS Kyoto, 1988.

Philip H. Swain. Baynesian Classification in a Time- varying Environment. Technical Report 030178, LARS Purdue University, 1978.

Fangju Wang. Fuzzy Supervised Classification of Remote Sensing Images. IEEE Transactions on Geoscience and Remote Sensing, 28(2):194-201, March 1990.

L.A. Zadeh. Fuzzy Sets and Their Application to Pattern Classification and Clustering Analysis. In J.van Ryzin, editor, Classification and Clustering. Academic Press, 1977.