Knowledge-Based Classification of an Urban Area Using Texture and Context Information in Landsat-TM Imagery

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ABSTRACT: A satellite image classification methodology using an expert system approach which incorporates information of texture and context as well as reflectance characteristics is described. The classification algorithm, which is coded in Prolog and C, is intended for use on Landsat-TM images covering urban areas. It constitutes a framework for experiments with different types of classification rules, with the possibility of using "quantitative knowledge" as well as more informally stated "heuristic" assumptions reflecting the human interpretation process as classification criteria. The main components are

- Intelligent detection of roads and linear structures which define image segments;
- · Computation of features, including texture, for image segments; and
- Final classification using an expert system approach.

The classification procedure is tested using a Landsat-TM image covering the central parts of Bangkok, and the resulting map has an acceptable accuracy in view of the spatial resolution of the data.

INTRODUCTION

 $T^{\rm HIS \ PAPER \ REPORTS}$ on the development of a methodology - using an expert system approach - for producing land-use maps of urban areas based on spectral, textural, and contextual information in Landsat-TM images. The overall purpose of the study is to establish a basis for examining the potentials of using satellite images as an information source for land-use mapping in the context of urban planning, especially in the Third World where the spatial expansion of major cities makes the use of satellite images desirable.

Aerial photographs, which have been a primary source of spatial information for urban areas, are superior to satellite images in terms of spatial resolution. The major drawback of aerial photographs is, however, that the cost per unit of area is high and that they have to be interpreted manually which, for a large city, is a task of considerable size, involving the work of a group of people for several months. There is a risk that the interpretation will vary between interpreters, thus producing an inhomogeneous classification result. On the other hand, the digital form of the satellite images makes it possible to use faster automatic or semi-automatic classification algorithms which use information from all spectral bands available at one time.

Use of satellite images is thus expected to provide a better understanding of the major development trends of large Third World cities, as a consequence of the improved possibilities for fast updating of spatial information, change detection, visualization of results, etc., which it presents.

URBAN LAND-USE MAPPING

SPATIAL RESOLUTION REQUIREMENTS

The following discussion is based on the Landsat-TM image (spatial resolution 30 m by 30 m) which was available for this study. Images from the SPOT satellite are, however, expected to produce better results due to the improved resolution of 10 m by 10 m for panchromatic images and 20 m by 20 m for multispectral images.

It is evident that a relation exists between the spatial resolution of the satellite image and its value as a data source for a given classifaction. It is reasonable to distinguish between two main types of approaches to the classification of a digital image:

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(1) Synthesizing: the purpose is to retrieve overall information regarding the major spatial trends in the image (e.g., the extension of residential areas); and (2) Analytical: the purpose is to register detailed information of the smallest elements in the image (e.g., housing units). According to Welch (1982), a spatial resolution of 5 to 10 m is required for accurate mapping of urban land use in Asia on this level, and it is reasonable to assume that the Landsat-TM image is generally inadequate for an analytical classification of the large Third World cities. However a recent land management study of Bangkok (Angel, 1987) clearly shows the need for land-use classification on different levels in a planning context. The scope of this land management study covers (a) general aspects of physical urbanization which require a spatial resolution where urban and non-urban areas can be separated; (b) assessment of the location and expansion of the formal housing stock which requires a spatial resolution where urban areas can be divided into areas with identical types of housing; and (c) assessment of the location of slum and squatter settlements, and estimation of population living in such areas, which requires an even better spatial resolution.

It can be concluded that the spatial resolution requirements, as defined by planning needs, cover a broad range. It is therefore likely that the synthesizing classification, expected to be possible from Landsat-TM satellite images, is able to present relevant information, although the spatial resolution of the data source is limited.

TEXTURE

The built-up areas of big cities constitute spectrally heterogeneous land-use classes, and it is not possible to make an accurate classification by examining the reflectance properties of each pixel in isolation from the neighboring pixels. The more detailed the satellite images get as the technology improves, the more "confused" is the pattern that characterizes the different land-use classes. Higher spatial resolution must, however, be regarded as a way of increasing the level of information in the image. Consequently, image processing algorithms are needed which are capable of extracting relevant information from the complex pixel patterns that characterize different parts of the city. The use of texture, i.e., the "visual impression of roughness or smoothness created by some objects" (Colwell, 1983), for the classification of urban areas has been described by Jensen

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(1979,1982) and Conners et al. (1984). A similar approach is adopted for this study which aims at examining small segments of the urban scene as entities and classifying these entities on the basis of the local texture, as well as the reflectance characteristics (the "color") of the segment. The previous remarks relate to those parts of the satellite images that represent builtup urban areas. Some parts of the urban scene, e.g., water and parks, must be treated differently. Those areas can be identified easily based on the spectral reflectance measured "per pixel." The difference between classifying built-up areas compared to water and green areas is that the former are characterized by the heterogeneity of the pixel pattern in the local area, while the latter are characterized by homogeneity. In other words a pixel with the unique spectral reflectance of green vegetation cover can be classified as such only if the pixels in the neighborhood are similar. If not, the pixel is a small part of a heterogeneous built-up area which must be classified based on the texture as well.

Texture can be computed in many ways (see, for example, Van Gool *et al* (1983)). The spatial grey level dependence method (SGLDM), which is a widely used approach, requires the computation of a so-called co-occurrence matrix. This matrix holds information about the probability of moving from one pixel value to some other pixel value in an image region, if the movement has a certain direction and length controlled by a "displacement vector." Several texture measures, each describing some properties of the texture, can be extracted from a given co-occurrence matrix (see, for example, Conners (1984)).

The main problem associated with the use of texture measures is that the image segment over which the texture is computed must be of a certain minimum size and ideally contain only one texturally homogeneous land-use class. A large segment will enable the most reliable computation of texture, but will also cause "edge errors" to increase if the texture computation by mistake is extended to the neighboring land-use classes. A small segment, however, may result in unreliable, random texture measures.

SEGMENTATION

The segmentation of the satellite image into texturally homogeneous segments is required to produce an accurate result, but difficult to accomplish, especially in a complex urban scene. A variety of image segmentation techniques exist, some based on initial regions using split-and-merge or region growing, and some based on the detection of edges between regions (Haralick and Shapiro, 1985).

An edge detection segmentation method, using the backtracking abilities of the language Prolog, will be described below, constituting the first step of the proposed classification procedure. The aim of this method is to identify linear structures, e.g., roads, in the scene, which, in addition to water and green areas, are used as borders between segments. This approach implies that areas surrounded by such objects tend to have homogenous textures which is, of course, not always true. The degree of success depends on the actual object for the classification, the purpose of the classification, and the classification system used. The approach is expected to be best suited for a synthezising classification approach which shows the predominant land use of relatively large regions of the city. The proposed method cannot be regarded as generally applicable, and forthcoming research will hopefully show how other methods, possibly "knowledge-based," can be included in the segmentation process.

CONTEXT - A HEURISTIC APPROACH

One purpose for this study is to examine whether it is possible to improve the accuracy of the classification result by using information about the context of a given segment during the classification process. This context information could be incorporated, for example, by determining the location of a segment relative to known objects in the urban scene as, for example, the city center, or by allowing the classification of other segments in the neighborhood to influence the classification of a given segment.

The problem with this approach is, obviously, where to start, if the classification of each segment is dependent on the classification of the rest. One solution to this problem, described by Wharton (1987), is to use an iterative classification algorithm in which the land-use map resulting from one step is evaluated and used to control the behavior of the next step. Context can also be incorporated by the use of a scene model describing the expected connections between the different elements in the scene (Nicolin and Gabler, 1987).

This incorporation of context emphasizes the need to express *a priori* knowledge of the object in a heuristic manner. Meisel (1972) describes the heuristic approach compared to the traditional: "heuristic approaches allow the utilization of knowledge of the particular application in question to minimize sample requirements and improve accuracy. . . . The heuristic approach is to define features with clear interpretations and, rather than using labeled samples to derive decision boundaries, to describe from knowledge of the problem the exact equations and logic of the decision rules." Naturally, when using *a priori* knowledge and models in this way, one should be careful not to implement one particular solution into the system before the actual image processing is started. The use of heuristic rules should only be used qualify the possibility that a classification attempt is proceeding in the right direction.

AN EXPERT SYSTEM APPROACH

PROLOG

The language Prolog is well suited for the development of image processing programs which use knowledge representation and inference engines reflecting an expert system viewpoint. Furthermore, Prolog is well suited for prototyping, i.e., fast implementation of new ideas for the purpose of testing. Prolog programs consist of facts and rules corresponding to the formal knwledge base of the expert system. When the program is run, a "goal" is evaluated using deductive reasoning. The Prolog rules may be expressed recursively, e.g.,

is_class (Segment_N , class_A) :texture_is_right, neighbors (Segment_N, Segment_N1), is_class (Segment_N1, class_B).

This rule expresses the assumption that segment_N belongs to class_A *if* it has the right texture *and* if segment_N1, a neighbor segment, belongs to class_B. This way of expressing decision rules recursively can be used to produce an image classification method with some similarity to the rules used by the human interpreter who sees the scene as an entirety, classifying each part on the basis of an evaluation of the surroundings.

It is evident that Prolog-based expert systems have the potential of introducing a more "intelligent" way of classifying a digital image. The actual implementation of a system does, however, require considerable creativity in order to formalize relevant and useful classification rules.

KNOWLEDGE-BASED CONTEXTUAL CLASSIFICATION

In the following the development of a prototype classification procedure will be described. This prototype should be able to handle knowledge of various kind which is considered relevant for mapping urban areas. It is regarded as essential that "quantitative" knowledge as well as informally stated "heuristic" assumptions can be used as classification criteria. The image processing system used is an IBM-AT equipped with a Revolution No. 9 card, a display, and the public domain CHIPS image processing software developed at the Institute of Geography, University of Copenhagen, which is intended for low-cost image processing in the Third World (Holm *et al.*, 1989). The expert system parts of the prototype are coded in Turbo Prolog while the low-level functions are coded in Turbo C. The integration of Prolog and C, i.e., calling low-level functions coded in C from Prolog, is quite straightforward, and this combination of a "descriptive" language with built-in abilities for deduction with a fast and efficient language like C seems to be very well suited for experiments with image processing expert systems. The main components of the classification procedure are

- (a) Per-pixel classification of homogeneous areas, e.g. water, with distinct spectral properties;
- (b) Intelligent detection of roads and linear structures which delimit image segments;
- (c) Computation of textural, spectral, and contextual features for each segment; and
- (d) Knowledge-based classification of the segments, taking into account the context of the current segment within the image.

STEP A: WATER AND VEGETATION

As mentioned above, water and vegetation areas must have a minimum spatial extension to be regarded as separate classes. To identify these areas in the satellite image, a simple spectral expert system (decision tree) is constructed, based on an examination of the properties of areas typical for the classes. Water is easily identified by its low near-infrared reflectance. The classification rules listed in Table 1 identify most of the water areas while only a few non-water pixels are misclassified. Green areas are identified by a high near-infrared reflectance. The classification rules are based on the "grass vegetation" rules of the expert system developed by Wharton (1987), which show good results. The introduction of rule 4 (Table 1) has the effect that only major areas covered with vegetation are accepted while the smaller plots surrounding the housing units to a large degree are rejected.

The result of the spectral expert is further processed using a mode filter which determines whether the number of classified pixels in a window surrounding a center pixel is below or above a given threshold, changing the center pixel accordingly. This is done to ensure that only pixels which are part of a relatively large homogeneous area are accepted. Normally, the use of a mode filter will remove correctly classified edge pixels because the number of classified neighbors is too small. To avoid this, an edge-preserving filter is used which examines four subwindows situated in each corner of the original window. The classification is accepted if the homogeneity criteria are satisfied in just one sub-window, assuming that this window is inside a homogeneous region while the other sub-windows may lie outside.

STEP B: ROAD DETECTION

This study evaluates a line-based segmentation approach. The aim is to detect roads, channels, etc., which are used as borders between segments. Ideally, the scene should be split into a number of polygons completely surrounded by borders, except

TABLE 1. CLASSIFICATION RULES FOR WATER AND GREEN AREAS. C = LANDSAT-TM CHANNEL.

water :	C4 < 45,	(1)
	C5 < 35.	(2)
green :-	C4 + C5 > C2 + C3 + C7,	(3)
	C4 > C5	(4)

at the edge of the scene. This means that only roads which are part of a primary road system should be used.

The road detection algorithm is started from a pixel in the image which initially is identified manually as part of a road. The algorithm seraches a number of directions within a certain maximum distance from this pixel for a new pixel which satisfies the criteria for being classified as road. These criteria comprise spectral homogeneity within the road segment and contrast to the surrounding non-road pixels. When a new road pixel is found, it is used as the starting point for further search.

The Prolog language is appropriate in this context because the built-in inference engine keeps track of which directions and look-ahead distances are tested and which are yet to be examined. When a road has been tracked to the end point, or the border of the image is reached, the program backtracks along the road to pixels with untried directions.

In order to minimize the number of small road pieces "sticking out" from the primary roads, it is decided that a road must have a certain minimum length; otherwise, it is ignored. This will also limit the number of misclassifications.

The ability to reconstruct small invisible parts of the road is implemented by allowing the expert to skip a number of pixels during the search for the continuation. This "look-ahead" facility is made dependent of the current road direction, i.e., the direction a small road segment preceding the current road termination point. A greater look-ahead distance is allowed in the current direction than in any other direction. Table 2 shows the structure of the road expert program expressed in Prolog pseudo-code.

STEP C: FEATURE EXTRACTION

The next step in the classification process is to extract the textural, spectral, and contextual features describing each segment.

The textural features are computed using the Spatial Grey Level Dependence Method, and the first step is to generate the co-occurrence matrix. The information in this matrix is made available to the classification algorithm by computing various measures each of which contains relevant information extracted from the co-occurrence matrix. For this prototype, the following texture measures are used: inertia, energy, entropy, cluster shade, and cluster prominence. For a more detailed description of these measures, refer to Conners *et al.* (1984).

For this study, the co-occurrence matrices are calculated using

TABLE 2. ROAD DETECTION PROGRAM: PROLOG PSEUDO-CODE.

ge	pal
	input road start point,
	find_road (roadsegment).
fir	nd_road (roadsegment) :
	calculate current roaddirection,
	direction_to_next_try,
	distance_to_next_try,
	it's_a_roadelement?,
	draw new roadsegment,
	find_road (new_roadsegment).
di	rection_to_next_trv :-
	current direction or
	$\pm 1/-20$ off current direction or
	+/- 90 off current direction.
di	stance_to_next_try :
0.76.20	1-4 pixels ahead in current direction or
	1-3 pixels ahead off current direction.
it	s_a_roadelement :-
	road homogeneity > threshold,
	contrast to non-road $>$ threshold.

only one "displacement vector," which causes textural patterns with orientation as the only difference to be regarded as different. For some purposes this is not appropriate. However, in view of the relatively low spatial resolution of the image used, it seems that the problem can be ignored - the textural appearance of each class is practically rotation invariant - but it must be considered when using images with higher spatial resolution, such as SPOT satellite images or aerial photographs.

In addition to the texture measures, the feature extraction program computes the mean and standard deviation of the pixels in each segment in order to make spectral information available to the classification algorithm.

The contextual knowledge is incorporated using a relatively simple approach. The mean center coordinates of each segment are computed, and the neighborhood of a given segment is defined as all other segments with centers lying within a certain distance. This approach is easy to implement but has the disadvantage that the mean center of a large neighboring segment can be too far away from the center of the current segment to be included in the neighborhood. The mean center is furthermore used to compute the distance between each segment and one or more "key points," in this case, the city center, in order to include information about the location of the segment within the total scene.

The feature extraction program writes the data for each segment into a file in the form of a Prolog "fact" which can be read directly by the classification expert, for example,

polygon(11, f1, f2, f3 . . .).

where n is the number of the polygon and fx its features.

STEP D: THE CLASSIFICATION EXPERT

The aim is, as mentioned, (1) to be able to use knowledge in various forms and (2) to construct a system with clear, easily modifiable decision rules, i.e., with the potential of changing the combination of features characterizing a given class or the importance of a given feature. Table 3 shows the structure of the classification expert expressed in Prolog pseudo-code.

A recursive Prolog clause "classify_neighborhood" (Table 3) makes sure that every possible way of classifying a neighborhood is evaluated by computing a score using the formula derived

TABLE 3. CLASSIFICATION EXPERT: PROLOG PSEUDO-CODE.

goal	
consult (segment_fact_fil),	
classify_all_segments.	
classify_all_segments :-	
choose segment,	
classify_neighborhood,	
fail.	
classify_neighborhood :-	
/* This recursive clause makes sure that all possible ways of classi- fying the neighborhood is examined */	
find one neighbor segment within search distance,	
classify_segment,	
not (end_search),	
classify_neighborhood.	
end_search :	
whole neighborhood classified,	
compute total score,	
modify_score_using_context,	
save classification result if score is better than any other try.	
classify_segment :-	
compute score using the 'expert part'	
modify_score_using_context :-	
modification of score based on co-existence of classes in neighbor- hood or other heuristic knowledge of the object.	
	-

by Wharton (1987). The score is computed for each segment and reflects how well a given classification of the segment fits the decision rules for this class. The score for each segment in the neighborhood is accumulated to form the total score for this attempt.

After computation of the total score for the neighborhood, the score is modified based on heuristic knowledge of the expected properties of the object. The current segment is subsequently assigned to the class for which the context-modified score has the highest value.

The classification rules are based on an examination of training sites with spectral and textural properties typical for the given class and *a priori* knowledge of the expected location of the various classes in the scene and the possibility of co-existence of two classes in a neighborhood. The heuristic assumptions used for this classification, phrased in general terms, can be expressed: "it is unlikely that class X appears in the same neighborhood as class Y," "it is likely that segments in the same neighborhood belong to the same class" and "class X is often found at a distance NI to N2 km from the center of the city." The total score for a given attempt is increased if these assumptions are satisfied; otherwise, it is reduced.

This use of heuristic knowledge does not exploit its potentials. The primary purpose is, however, to give an example showing how this kind of knowledge can be incorporated in a contextural classification algorithm.

RESULTS AND DISCUSSION

In order to evaluate the performance of the proposed method, a Landsat-TM scene covering the central and northern parts of Bangkok has been classified. Plate 1 visualizes the steps taken during the classification process for a small part of the test area, and Table 4 shows the expression of the expert system rules for this specific purpose.

The city of Bangkok, Thailand, is used as an example of general trends in urban development in the Third World. Bangkok was chosen for the case study because the considerable size and the rapid spatial expansion of the city make the use of satellite images desirable. The developed classification prototype was evaluated using a classification system reflecting the information demands of the National Housing Authority, Bangkok, which is an example of a public institution involved in urban planning, especially the supply of land and housing. The intention was to use the land-use key of the "Bangkok Land Management Survey 1987" (Angel, 1987), but a visual interpretation of the satellite image revealed that it had to be somewhat modified. Plate 1 shows the modified land use key. It is difficult to identify the exact location of the slum and squatter settlements because of the inadequate spatial resolution of the Landsat-TM image and because these settlements are not as well delimited from the surroundings as the official map indicates. Instead, the classes 2 and 4 were defined in an attempt to single out areas with a high proportion of slum and squatter settlements. Class 6 is characterized by a very regular street pattern compared to class 5; and class 7, "Institutional buildings," originates from Angel (1987) and includes large buildings built by public and private organizations, as for example, government and university buildings.

As aerial photographs were not available, the result of the classification was compared to city maps, a visual interpretation of the satellite image, and general knowledge of Bangkok. The classification of vegetation and water which constitutes the nonurban classes was good. The classification procedure succeeded to a large extent in suppressing small vegetation-covered areas which are part of another urban class.

The road expert was tested using the TM channel 5, the single channel with the most distinct appearance of the roads. It was



PLATE 1. The steps of the classification procedure. (A) The original Landsat-TM image covering the central parts of Bangkok, December 1987. Channel 5,4,3 shown in red, green, and blue, respectively. (B) Classification of water and vegetation based on the spectral properties and homogeneity of an area. (C) Segmentation of the scene by detection of linear objects. (D) Knowledge-based classification of urban land use using texture, spectral, and context features.

The numbers of the legend refer to (1) Densely built-up areas. (2) Densely built-up areas with high proportion of slum and squatter areas. (3) Individual medium density housing. (4) Individual medium density housing with high proportion of slum and squatter areas. (5) Low density individual housing. (6) Low density housing: "land and house" projects or "land subdivision" projects. (7) Institutional buildings. (8) Homogeneous vegetation. (9) Water. (10) Roads and Shophouses.

not possible to detect every road in a scene starting from one single point, because too many misclassifications are made if the criteria for assigning the label "road" to a pixel are made too loose. When these criteria are tightened to produce more accurate results, a situation where no road continuation points can be found will occur more frequently. As one solution to this problem, the current prototype allows the user to place several potential start points in a file before the program is run. When the road expert is unable to establish the continuation of a given set of roads in any direction, it automatically backtracks and reads a new start point from this file until all points are used. It has not been possible to establish completely closed polygons in all parts of the image, and it has thus been necessary to make a visual interpretation and correction in some smaller areas in order to make the result acceptable for the next step in the classification process. An improved performance could be obtained if information from more channels were used for the road/non-road decision, but one has to recognize that the image simply does not contain information about the location of the roads in some areas.

Although the detected roads do not comply completely with the ideal given by a map, they do reflect the realities of the image and are in good accordance with the results of a human interpretation.

There seems to be a rather limited variation of texture within each of the established segments. This suggests that this segmentation principle is acceptable in the given context. At some locations, primarily in the transition zone between urban TABLE 4. DECISION RULES FOR THE CLASSIFICATION OF IMAGE SEGMENTS.

The following features are used:

Texture features:

T1,T2,T3,T4,T5 = Inertia, Energy, Entropy, Cluster Shade, Cluster Prominence.

Spectral features:

 $\overline{C1,C2,C3}$ = Landsat-TM channel 5,4,3.

Context features:

D = distance to city center.

Numbers in square brackets denote respectively supporting and opposing evidence which are used to compute a score reflecting how well a given classification attempt fits the rules (Wharton, 1987). This score is subsequently modified based on an examination of the neighborhood of the segment. The segment is finally assigned to the class yielding the highest score.

dense:-			
32 < T1	[10,10]	0 < T4 < 1000	[10,10]
0 < T5 < 150000	[10,10]	0 < C1 < 48	[10,5]
0 < D < 8	[0,20]		
dense with high pct. of sl	um:-		
40 < T1 < 70	[10,20]	1000 < T4 < 6000	[10,20]
250000 < T5 < 700000	[10,10]	0 < D < 11	[0,20]
0 < C2-C3 < 6	[20,10]		
medium density individua	al:-		
30 < T1 < 40	[20,10]	1.4 < T3	[10,10]
-500 < T4 < 4000	[10,10]	0 < T5 < 400000	[10,10]
0 < C3 < 52	[20,10]	0 < D < 11	[0,20]
0 < C3 < C2	[20,0]		
medium density individua	al with hig	h pct. of slum:-	
0 < T1 < 32	[10,10]	0.0013 < T2	[10,10]
0 < T3 < 1.31	[10,0]	0 < T4 < 1000	[10,10]
0 < T5 < 150000	[10,10]	0 < D < 11	[0,20]
0 < C2-C3 < 6	[20,10]		
low density individual:-			
30 < T1 < 40	[20,10]	0 < T2 < 0.0007	[5,0]
1.43 < T3 < 100	[5,0]	-500 < T4 < 1000	[10,10]
40000 < T5 < 500000	[10,10]	60 < C2	[10,10]
0 < C3 < C2			
low density, regular patter	rn:-		
30 < T1 < 40	[20,10]	1.43 < T3 < 100	[5,0]
1500 < T4 < 3000	[10,10]	200000 < T5 < 30000	[10,10]
60 < C2	[10,10]	0 < C3 < C2	[20,10]
institutional:-			
45 < T1	[15,10]	70 < T1	[20,0]
6000 < T4	[15,0]	700000 < T5	[20,10]
	Construction (17)		

and rural areas, the segments are too big and contain textural properties from different land-use classes. One reason for this is that the road pattern here is rather blurred; the local roads of these areas should be seen as parts of a residential land-use class, not as border lines between segments.

Misclassifications occur if the segmentation of an area is inadequate, but the expert system classification approach, based on texture and context, performs well when the given segment is texturally homogeneous. Bearing inmind the given segmentation, the result of the classification is satisfactory and shows that an overall, synthesizing classification of a complex urban scene can be made from Landsat-TM satellite images.

CONCLUSION

Image processing in an urban context is faced with some specific problems as a consequence of the heterogeneous nature of built-up urban areas. This paper proposes an expert system approach based on programs coded in Prolog in order to view the satellite scene more as an entity using contextual knowledge as well as textural information in the classification process, and to make a more flexible use of different classification rules possible. It is essential to acquire knowledge of how the structure of different urban areas is reflected in the texture of the image in order to be able to adjust the knowledge base of the expert system to meet a given classification objective.

The results obtained suggest that the idea behind the road expert is usable and that it is possible to detect roads by relatively simple contrast checks following a certain search strategy which is controlled by the recursion and backtracking mechanisms of Prolog.

The classification procedure must be regarded as a prototype, and further adjustment of the decision rules has to be made. Nevertheless, the proposed approach—computation of texture of segments reflecting the structure of the object, and the introduction of an expert system representation of knowledge seems to be able to produce useful results. In addition, the system constitutes a good framework for experimenting with different types of classification rules.

The use of data with higher spatial resolution, e.g., SPOT satellite images, is likely to improve the potentials of the method within the context of urban planning. It is evident, however, that a number of questions cannot be answered until the spatial resolution of the data source allows single housing units to be identified and classified.

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