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TOWARD AUTOMATIC EXTRACTION OF CARTOGRAPHIC FEATURES.(U)

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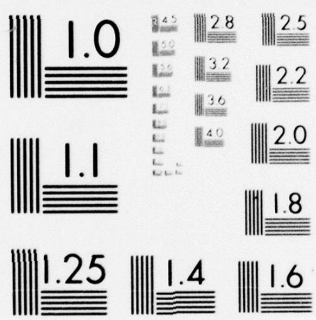

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TOWARD AUTOMATIC EXTRACTION OF CARTOGRAPHIC FEATURES

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July 1978

Contract Report

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Prepared for

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The problem of automatically extracting map symbology from source imagery is studied. It is concluded that a great deal of geographic knowledge used by humans, who currently perform this extraction function, must be made available to machines before the function can be automated. Several geographic knowledge sources are discussed and an attempt is made to define paradigms under which knowledge can be encoded and used in the computer. → next page

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cont. An automatic cartographic feature extraction system (ACES) is sketched which represents a best framework for continuing development on this difficult problem given current achievements. A systems approach is taken with first consideration given to desired outputs and available inputs. It is concluded that input/output technology is far in advance of technology available for interpretation of the data. Emphasis is placed on the use of knowledge by ACES during automatic interpretation of imagery. Many types of knowledge typically used by humans appear difficult to engineer into automatic processes. Use of positional knowledge encoded in a geographic data base (GDB) is selected as the most promising avenue. Proposals are given for future research work in that direction.

Abstract

The problem of automatically extracting map symbology from source imagery is studied. It is concluded that a great deal of geographic knowledge used by humans, who currently perform this extraction function, must be made available to machines before the function can be automated. Several geographic knowledge sources are discussed and an attempt is made to define paradigms under which knowledge can be encoded and used in the computer.

An automatic cartographic feature extraction system (ACES) is sketched which represents a best framework for continuing development on this difficult problem given current achievements. A systems approach is taken with first consideration given to desired outputs and available inputs. It is concluded that input/output technology is far in advance of technology available for interpretation of the data. Emphasis is placed on the use of knowledge by ACES during automatic interpretation of imagery. Many types of knowledge typically used by humans appear difficult to engineer into automatic processes. Use of positional knowledge encoded in a geographic data base (GDB) is selected as the most promising avenue. Proposals are given for future research work in that direction.

Toward Automatic Extraction of Cartographic Features

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1. Introduction

The processing of geographic data has reached a high level of automation. Automation has affected data gathering, data storage, data combination, and map compilation. Airborne sensors, such as those in Landsat, are collecting image data at an incredible rate. In order to process, combine, and exchange data, institutions in the field of geographic data processing are archiving image data and symbolic abstractions of it in digital computer useable form. Computer based systems have been built to provide the function of rapid map revision. Altering a map encoded in digital electronic storage requires only that the small number of changing features be altered in representation. Automatic drafting is readily available for producing standard map sheets from computer stored data.

There is one great bottleneck in automated cartography - - the symbolic features which are to represent raw input imagery must be extracted by human operators. Generally this is a tedious and time consuming process of identifying a feature to the computer and then manually tracing its extent on the source material mounted on a digitizing table. The remaining problem is therefore that of automatic extraction of symbolic cartographic features from source imagery. The payoff earned by solving this problem would be astronomical. There is a greatly increasing requirement for timely image analysis in order to manage earth resources, to monitor polution, to understand physical phenomena, to record and tax land use, to plan and assess the impact of construction projects, to provide reconnaissance in hostile areas, to manage agriculture, to monitor hydrology, etc.

While the promise is great and the search is intense, we are still far from a general solution to the feature extraction problem. There are many researchers in the field doing work under various titles such as pattern recognition, image or picture processing, computer vision, robotics, scene analysis, or artificial intelligence (A.I.). It is now apparent that the problem must be approached by taking many small steps since dramatic results have eluded the best of seekers for 20 years. One of the goals of the research reported here was to identify some of the steps to be tried as part of the overall solution to automation of feature extraction for cartographic compilation.

In order to understand the current state of automation in cartography and the position of feature extraction in it, a systems oriented approach was taken to structure the study. An assessment was made regarding what components of an automatic system are currently available and what components need to be created. The hypothetical system desired is called ACES for "Automatic Cartographic Extraction System". Output products desired from the system are discussed first in Section 2 along with current automation for producing them. Available inputs and devices for producing them are considered in Section 3. Section 4 gives a general discussion of components of ACES which must perform the transformation of data. The knowledge component necessary for ACES, currently supplied by humans, is studied in Section 5 and paradigms for applying knowledge in the feature extraction process is treated in Section 6. Section 7 presents a general overview of possible ACES process control. Outstanding problems requiring work are discussed in Section 8 and future research directed toward solution of some of these problems is outlined in Section 9.

A summary of the conclusions reached, discussed in Section 10, are as follows. The cartographic feature extraction problem is a difficult problem with difficult subproblems. Certain of the subproblems, such as registration and use of a geographic data base as a knowledge source, appear to have reasonable solutions. The engineering of knowledge for use in cartographic feature extraction is the key issue. No unified paradigm exists but several individual paradigms exist which potentially solve some subproblems. Dependence on the use of knowledge makes the ACES issue generic to other central issues of A.I. It is the most important issue and there is much useful work to be done on it.

2. Automatic Cartographic Extraction System Output Objectives

Since a system is originally conceived to satisfy some specified objective, it is best to begin by noting **the** desired products which the system is to produce. There are several products which we could expect from ACES. First of all, we would like to produce standard cartographic sheets and thematic maps and overlays. Secondly, we would like to create special non standard products of the same general kind by quick compilation from the standard digital data base. Thirdly, there is great interest in creating digital data bases to be used by other automatic systems. Such systems include navigational systems and enviromental or traffic modeling systems.

Even the production of thematic maps requires some interpretation and symbolization of data: thus it can be assumed that all ACES output is in digital form. Map sheets may be created from digital ACES output products by D/A conversion such as plotting. Thus, because of the interpretation and symbolization ACES must perform in processing data, it follows that ACES logic will all be digital and that all analogue inputs must be converted before interpretation. The general ACES objective is therefore to create digital data bases. The exact format of the data bases is left undefined in this report, but Sections 4,5, and 6 discuss in some detail types of information to be stored. Format will vary according to the process that consumes the data. In particular, ACES will be one of the larger users of its own product due to the fact that it must use stored knowledge to aid in interpretation of new input imagery.

2.1 Cartographic details: resolution, scale, and positioning

Aerial imagery is already a primary input source for map making as well as for land use classification. Most map compilation techniques have used human interpretation and human mensuration of the input data. The level of automation is, however, steadily increasing. For instance, it is now possible to make elevation maps semi-automatically from stereo imagery in a production shop. Thematic maps of ERTS imagery are also commonly produced. Although there are differences in data collection techniques between airplane and satellite surveys there are no conceptual differences between them from the standpoint of automatic map compilation.

It is assumed that input to an automated cartographic system is a matrix of spectral signatures collected from some "rectangular" window of the earth's surface. The problems of restoration and geometric transformation necessary to produce the input matrix are not addressed here. (There is evidence that these problems have acceptable solutions in the interesting cases.) For practical purposes an aerial photograph can be regarded as a matrix of infinitely many spectral samples of the earth's radiance. For digital processing, however, the window is represented as a matrix of m rows and n columns of <u>pixels</u> each of which is obtained by integrating continuous radiance samples over some grid cell or <u>resolution element</u>.

It is not necessary to produce photographs for automatic mapping. It is quite common for imagery to be converted to digital form at the platform (plane or satellite) and transmitted to earth. The ERTS-1 satellite sampled and transmitted spectral signatures of 60 meter (m) by 80 m units of the earth's surface. Seven million of these units created a digital image, or frame, which represented a window of roughly 185 km by 185 km on the earth. Various sizes of resolution elements are possible depending upon the height of the imaging platform and sophistication of equipment. Weather satellites deliver resolution elements 800 m on a side while Skylab cameras are capable of 12m units.

Digitally produced maps should have a map resolution of 0.05 mm based on the experimental evidence that a human can resolve 10 line pairs per millimeter. The experience of the Defense Mapping Agency Topographic Command confirms this estimate: a grid spacing of 0.004 in. ≈ 0.10 mm was found to be too rough for the eye while 0.002 in. ≈ 0.05 mm was suitable. Maps output by the GISTS (Graphic Improvement Software Test System) system at DMATC (See Burdette et al., 1973.) can be viewed as very large matrices of 2^{14} by 2^{14} resolution elements.

Accepting 0.05 mm = 5×10^{-5} m as the required map resolution yields a simple relationship between map scale and ground resolution.

$$R_g = 5 \times 10^{-5} S_m \qquad \text{(Eq. 2.1)}$$

where R_g is ground resolution in meters and S_m is map scale. (See Doyle, 1973, for a similar development.) Taking ERTS resolution to be 70 m on the ground, a map scale of 1:1,400,000 is appropriate for a 1 to 1 correspondence between ground resolution elements and map resolution elements. Deviation from this scale toward smaller scales (i.e. 1:5,000,000) implies a waste of sampling and storage effort while deviation toward larger scales (i.e. 1:25,000) implies errors in representation.

Each point on the earth's surface can be assigned a <u>position</u> with respect to some local or global coordinate system. U.S. map accuracy standards specify that the standard error for point positions should not exceed 0.3 mm on the map. Thus the point positioning accuracy limit for a mapping technique is as follows.

$$\sigma_p \leq 3 \times 10^{-4} S_m \qquad \text{(Eq. 2.2)}$$

where σ_p is the standard error in meters and S_m is the map scale. (See Doyle, 1973.)

<u>Ground control points</u> can be positioned from low altitude photography to within 1 m and from ERTS imagery 50 m accuracy can be achieved (Van Wie, 1977). This is good enough for current purposes and is likely to be further improved with the future placement of navigation satellites. According to Doyle (Doyle, 1973) the type of photographic equipment in the Skylab satellite is capable of 12 m ground resolution and 10 m positional accuracy, which nearly allows compilation of maps of scale 1:25,000 if equations

2.1 and 2.2 are checked. While this map scale is not large enough for reconnaissance or tax assessment purposes it is sufficient for a large number of applications. With 1 m resolution and 1 m positioning nearly all types of maps could be produced.

2.2 ACES output products

It was previously stated that there are 3 general classes of output to be generated by ACES. The first of these classes contains standard cartographic sheets and thematic maps. Section 2.1 concluded that maps of scale 1:25000 could currently be compiled using satellite platforms and that scales as large as 1:2500 were probably achievable with military satellites. Once cartographic feature extraction is accomplished with the symbolic results stored in computer readable form, many specialized products could rapidly be produced. Special hill-shading techniques could be used, for instance, to dramatize relief for pilots about to fly over a given area at a given time of day. Thematic mapping, made more popular by the advent of Landsat, is a convenient way of using the grid-cell method of land feature symbolization. Lending themselves readily to automatic classification, thematic maps indicate the land class of each ground resolution element without much consideration of its relationship (local or global) to other elements. The global feature structure of the mapped terrain is not symbolized in the computer data base but hopefully will be supplied by the perceptual system of the human user of the map.

Once geographic data is compiled and archived, it will be possible to rapidly produce special products by selection and combination. For example, an engineer may have the need to know all parts of a region where ground elevation is less than 1200 feet. A two-color thematic map generated from an elevation matrix might satisfy his requirement. As another example, a military commander might want to see a "contour plot" of a trafficability function t(x,y) indicating the mechanical properties of the soil in a given region. Such special products could be generated from ACES archives as the need would arise and would not necessarily impose any considerations on the system design.

ACES archives could also provide digital data bases for other automatic terrain analysis systems. For instance elevation matrices and drainage features compiled in ACES could be input to hydrological modeling programs. All features might be necessary as input to a trafficability program whose job it is to find the best path of travel for a truck going from point A to point B. As yet another example, two archived maps of the same area made for different dates could be compared to produce a map of change. These uses of ACES data do not really depend on automatic feature extraction and are currently possible with current geographic data base systems which depend on human feature recognition.

2.3 ACES performance: cost and quality

Past automation techniques have already shown that acceptable quality can sometimes be maintained with possible cost reduction. Cost can be measured in dollars, in time, or in the number of errors in the product. Quality is currently dependent on human feature extraction: automatic elevation contouring, for instance, does not produce results as satisfying as those done by a cartographer. It will probably remain true for some time that automatically compiled products will be noticeablly more coarse than those done by humans and that progressive refinement will cost more and more to achieve. One answer to this problem is to economically produce the coarse maps knowing that human consumers have the perceptual capability to smooth the interpretation when necessary. The thematic maps produced automatically by EROS from LANDSAT imagery exemplify this philosophy. Achievment of good quality mapping by automatic means regardless of cost is an important research goal. If and when that goal is reached, another period of development will be required to produce that quality at a cost competitive with present manual methods.

2.4 Output devices and techniques

Various sophisticated devices are currently available to meet map accuracy standards in production plotting or to allow graphic interactive exploration of a geographic data base. Production output devices include random vector plotters (drum or flatbed), raster plotters (drum or flatbed), and electron beam recorders. Both raster and vector plotters can output a 5×10^6 symbolic point map at 0.002 inch resolution in less than two hours. The choice of a particular output device will depend upon further reproduction steps. Currently there is a trend toward raster plotters and away from established vector plotting.

There are algorithms for converting between symbolic raster and vector representations which present no problems in batch mode(i.e. in production mode). However, for graphical presentation to an interactive human, the conversion algorithms are time consuming. If the geographic data base (GDB) uses vector representation, a sort (and perhaps broadening) is required for raster presentation. If a raster representation is stored, then a tracking (and perhaps thinning) operation is needed. Accessing and converting the data in this manner places a bottleneck in the system, not only for geographical output but also for delivery to data processing programs which operate with a representation other than that used in the GDB. There is no apparent solution to this data representation problem other than bearing the cost (in time and processing) of conversion because neither raster nor vector representation is sufficient for all processing and it seems futile to maintain data in both forms.

Section 3 discusses input devices which often double as output devices, so further discussion is deferred until that section. A similar assessment is made for both input and output technology - - the current capabilities far exceed the current capability to meaningfully interpret the data automatically.

3. System input requirements

In order to derive the geographic data products discussed in Section 2, ACES must be provided with varied input. Several forms of input are necessary, the most obvious of which is aerial imagery containing current sensor information. Other inputs are base maps and names which are not apparent in imagery and knowledge for interpreting image data. Knowledge may be implemented by a combination of software and data base or by an interactive human analyst.

3.1 Aerial imagery

Up-to-date geographic information is easily obtained via aerial imagery from a variety of sensors. Black and white stereo photography has been the most common form in the past but other sensors such as infrared and radar are gaining in use. Multispectral imagery, where a set of registered images from different sensors is produced, has been the subject of intense effort since 1972 due to the LANDSAT program. Due to the limited use of knowledge by automatic processes relative to human photogrammetrists it appears that multispectral imagery will be preferred for some time to come in automatic analysis tasks. Major problems in using multispectral imagery are 1) registration of sensors, 2) different resolution of sensors, 3) low resolution of some sensors, and 4) high volumes of data. Huge amounts of B&W photography are gathered and analyzed for current information needs.

It is estimated that the Air Force alone obtains 10 million pictures each year. Thus the tremendous momentum of current manual procedures will surely influence future experiments in automatic methods.

3 1.1 Black and white stereo

Black and white (B&W) stereo photography is the most common input to map compilation. Highly developed hardware/software systems exist for rapid extraction of information. Equipment such as UNAMACE [UNAMACE 1968] exists for nearly automatic extraction of elevation matrices from stereo pairs. Extraction of features such as road or drainage networks or vegetation windows is manually guided. While the human provides the pattern-recognition and processing control capabilities the machine handles rectification, coordinate transformation, and digital storage [Dubuisson 1977]. Automatic extraction of elevation data is successful because it depends only on low-level techniques which correlate images taken under almost identical conditions and which are already approximately registered according to flight control information. Even so, extraction of elevations in uniformly textured regions, such as forests, can be difficult and errorful. It would be a great accomplishment if automatic tracking of lineal features in B&W photography could be achieved. Knowledge more sophisticated than a stereo model surely will be required. A proposal for using an existing map and elevation data for automatic tracking of drainage is discussed in Section 9. In general analysis of B&W imagery requires the use of large neighborhoods and global knowledge - - appropriate for human analysis, problematical for automatic analysis.

3.1.2 Multisensor imagery

The chief characteristic of multisensor imagery is that for each small geographic neighborhood several signals are available which when combined give strong indication of the material being viewed. Knowledge of the material present at geographic position (x,y) allows for simpler tracking of cartographic features than is possible with B&W imagery. Unfortunately, there have been few experiments reported where attempts were made to automatically track lineal features in multisensory imagery. This is due in a large part to the concentration of research on low resolution LANDSAT data where most cartographically interesting lineal features are beyond recognition. Higher resolution multisensory imagery is not readily available - - certainly not to the academic community.

Collecting multisensor data is not as simple as gathering black and white imagery. Multispectral sensed data (MSS) is gotten by splitting a beam of light reflected from earth element (x,y) and filtering the branching beams to get tonal samples in each of the bands. Accurate registration is assured by beam splitting. If different sensors or different platforms are used registration becomes more difficult. Radar and infrared sensors have lower resolution capabilities than visible light and this presents additional problems. A vector of tonal samples can, however, be derived for each earth element (x,y) in an output grid by using a transformation system as implemented in DTEDS[Jancaitis 1977] or DIRS [Van Wie,1977].

To do this separate coordinate transformations $T_i(x,y)$ must be gotten for each band i of sensory input. Some interpretation of each image i is necessary to arrive at T_i, such as specification of control points or recognition of structural features. This presents no theoretical problem but can result in a great deal of computation in practice.

3.2 Cartographic name file

Names of geographic features are abstractions and are not at all evident in aerial imagery. Yet, names are essential for recognition and communication in geographic displays. Names are really tags for concepts which include both qualitative and quantitative information. For instance the name of a city could evoke a latitude and longitude, a population, an elevation, an average temperature and rainfall, political entities, etc. A name often links to other names; for instance, Philadelphia is in the state of Pennsylvania, located on the Delaware River, and has Rizzo as mayor. There appears to be no end to the complexity which name concepts can create and no unique way for organizing name data for storage and retrieval.

For standard cartographic expression file formats for name data can be established. U.S.G.S. has developed the GYPSY system [Orth 1974] for storage and retrieval of name data. Clearly only minimal information must be stored with a name for use in creating standard map symbolization. For instance, for small towns the geographic coordinates and population should suffice. However, to provide for creation of specialized thematic products it may be important to have information items such as amount of electricity consumed, type of water system, number of Exxon service stations, or percentage of the population under 40. Clearly some range of output products must be specified before a practical data base can be established.

Names can be attached to any of the three basic geographic data types - - points (i.e. a mountain peak), lines (i.e. a river), and regions (i.e. a desert). Names will be absolutely essential in symbolizing output displays. The concept associated with the name is likely to be useful in interpretation of imagery which might affect other symbolization on the map. For instance, knowledge of the location of a large city might cause other interpretation and symbolization to be suppressed within a specified region of the imagery. Theoretically the opportunities for applying a priori knowledge stored in a file of named geographic objects are unlimited, however, in practice only very constrained uses are likely to prove possible.

3.3 Base maps and bootstrapping

Stored base maps will be an essential component of any ACES type system. Base maps can be thought of as skeletons on which the flesh of current detail must be hung. The source of the detail is aerial imagery and its content will be specific to the display task. Base maps are available at some scale in digital form for all major political divisions of the world. Important cartographic detail such as water bodies and major roads should also be readily available [Robe 1974].

Registration is the key to the storehouse of knowledge in the base maps. Major features apparent in the imagery must be brought into correspondence with mapped features. The base map could then be used as a guide for a more detailed analysis of the imagery. Lineal networks, such as roads and drainage can be searched for connecting features which are evident in the imagery but were either not previously present or were ignored during base map compilation. In this manner initial manual mapping effort can be used to guide automatic compilation of detail and change. Similar to a bootstrapping operation, successive iterations could yield better and better results in an increasingly automatic mode.

Eventually base maps (or map data base) could be at the same level of detail and same resolution as the desired output product. Quite specific changes could then be sought for display and for base map update. For example, water body boundaries could be monitored for change, urban lots could be checked for change in useage, or the progress of clear-cutting a forest could be recorded. The underlying assumption is that enough of the scene remains constant for reliable registration and calibration. Changes could then be detected automatically by observing differences in some of the regions mapped in the data base from those observed in the imagery.

3.4 ACES knowledge base

It is clear that use of real world knowledge will be necessary for an ACES type system. Sections 3.2 and 3.3 have already introduced mechanisms for applying a priori, or stored, knowledge to automatic analysis of aerial imagery. A detailed categorization of knowledge forms available to ACES is attempted in Section 5. At this point it is useful to specify the two general knowledge forms which must be input to ACES.

First of all ACES should have a declarative knowledge base: this is essentially a geographic data base encoded as data. Present cartographic data bases exist in declarative form such as GISTS [Cook 1974] or DIME [Silver 1977]. In both cases the knowledge is very static and is essentially a digital icon of a hard copy display. As discussed in Section 3.3, however, the static geographic data base can be a powerful source of locational knowledge when coupled with registration and procedural knowledge techniques. Procedural knowledge is implemented through programs. To some a distasteful knowledge encoding technique, embodying knowledge in procedure is sometimes the only way to approach specific or complex contexts or actions.

Signal prototypes or discriminant function coefficients could be stored as data for later use in classification of land elements. This is an example of declarative knowledge encoding. On the other hand, for processing drainage networks the knowledge that "streams flow downhill and intersect other bodies of water" is perhaps best embodied in the code of a tracking algorithm. Proponents of syntactic pattern recognition might argue that the tracking decisions can be encoded as a grammar and hence as declarative knowledge, but there is no evidence that more practical results will be obtained. Knowledge encoding and use is a primary research topic in A. I. today with few definitive conclusions reached. Further discussion is reserved for Section 5.

3.5 Human knowledge resource

It is inconceivable, given the present state of the art, that a system such as ACES could be designed without primary consideration of human input. In many tasks involving visual recognition and the use of inference the human is still more reliable and faster than a computer. There are some interpretive tasks which we do not now know how to encode in terms of computer operations. Generalization and artistic rendition of graphical data are two such tasks.

Although it is clear that human input is necessary to ACES it is not clear how that input will control, be controlled by, or cooperate with a computer system. Some successful work has been done on this [Barrow 1977, Ryan 1974] in specific circumstances but general interactive cooperation between man and machine has not yet been realized.

In typical "automated" cartographic installations the human performs all feature recognition operations at the point of data entry - - i.e. during digitization. It is exactly this laborious task which we want to automate in ACES. Another typical human function performed in today's systems is that of editing cartographic data bases for error - - error introduced in the manual digitization input process! One currently feasible mode of operation for ACES would be to have ACES perform automatic extraction and digitization and then present its results to the human as an overlay on the source imagery. The human can then edit the machines work instead of his own. If the amount of editing were small this scheme would represent another positive step toward automatic compilation. In any case the human can apply whatever knowledge he has and need not even be conscious of it.

3.6 Input devices for ACES

The important conclusion here is that input device technology is far in advance of our knowledge for using the data which it delivers. An exciting array of devices are now available which offer a range of design choices.

- There are off-line devices for delivering billion bit representations of an entire source document and there are CRT graphics systems which permit human editing of local features.
- There are devices which uniformly sample the entire source image and there are those which can selectively sample specific areas selected by intelligent processes.
- There are devices which can organize samples as 2-D or 1-D arrays or as random sequences of points.
- There are devices that can scan optical images, electronic images, or images recorded on paper or film.
- There are devices that can vary their resolution and there are devices that can be calibrated and controlled to sense different spectral bands.

The three sections below describe some available input devices according to whether they sample the input in 2-D, 1-D, or randomly. This breakdown may or may not be meaningful depending on the overall philosophy for analyzing the data produced as is discussed in Section 3.6.4

3.6.1 Matrix input devices

Source material can be sampled simultaneously in 2-D by an array of photodiodes. 50x50 elements with 1 mil spacing were available on a single chip in 1974 [Snow 1974]. Dynamic ranges of 1000:1 are possible. The chief advantage of true 2-D sampling is stable geometry with totally electronic sampling. However, most source imagery will be larger than any practical photodiode array so other scanning techniques will still be necessary to move the array with respect to the image, or visa versa. Some of the speed gained by parallel sampling may be lost because of sequential I/O to a digital computer. The arrays have serious potential if pattern recognition hardware is placed between them and a digital computer.

Another parallel 2-D sampling device is the ROSA equipment [Lukes 1978] which delivers sampled spatial frequency for a given window of the source data. Its utility lies in recognition decisions best made in the Fourier domain. As with photodiode arrays, the window of data viewed by ROSA is small relative to the entire source material and other scanning techniques must be used for positioning.

3.6.2 Raster devices

Raster devices organize input samples into a sequence of rows of samples, each row itself being a sequence of samples in time. Thus there will be a total linear ordering induced on the set of image samples. Raster scanning (plotting) implies that each pixel is considered once and only once and hence scan (plot) time is constant regardless of image content. This is the chief characteristic of raster devices and places them in stark contrast to random linear devices. Raster scanners can cover a source area of 120 cm by 150 cm at 0.0025 cm resolution in 30 minutes with black and white output or 3 hours with 5 bit color/texture output. At 0.0025 cm resolution 3 billion pixels result. The devices just described are clearly for operation off-line to data analysis and not intended for interaction.

3.6.3 Linear input devices

Linear input devices are built to trace linear features in two dimensions. Their output is a collection of curves which creates a sparser and more highly organized model of the source data than is created by matrix or raster scanners. The most common equipment type is the "digitizer" which has a positioning head that is guided over the features by a human. The position of the head is known by the machine via mechanical tracking or by sensing a location on a grid in the table under the head. While the operator moves the head along the feature the machine records the path of positions by sampling in either time or distance intervals. By using such devices, all feature recognition is performed by the human before data is entered into the computer.

Automatic feature recognition is possible and the human may be omitted from the linear input systems. Research is continuing "along this line" including the research summarized in this report. Apparently i/o Metrics has had a system for some time that can follow lineal features on map sheets [Wohlmut 1974]. Once on a point of a line, a circular neighborhood around the point is scanned to determine the next point of the line. The equipment then repositions to the new point found and continues. An area of up to 5 ft. by 5 ft. can be scanned with 5 to 10 mil increments typically used. The claim is that problems of noise spots and intersections are solved. It must be emphasized that this equipment was designed for scanning existing map sheets and not imagery so that the source data is idealized and clean.

Preliminary work [NASA, 1977] has shown that some linear features can be traced in real time at the platform. Success was reported in the tracking of major land-water boundaries using MSS data. It would be quite a breakthrough if performance could be extended to many features. The real-time constraint can be dropped and geographic data base knowledge can be added to the tracking process. Thus there is some reason to be optimistic. The major payoff in this kind of operation is that feature recognition is done at a very early stage eliminating the need for 2-D image storage and processing. It is easy to imagine software interacting with an analogue source eliminating large amounts of redundant intermediate digital data storage.

3.6.4 Discussion of input concepts

For a system that scans off-line and then processes digital information in batch mode the previous distinctions made for input devices are irrelevant. All of the source data must be scanned because the analysis necessary to confidently ignore parts of the data is decoupled from the input operation. Similarly there is no meaningful control over resolution. The time sequence and organization by which samples were taken is likewise not meaningful - - data storage organization, quite a different thing, is of prime concern. Such off-line systems are typical of the day. They impose more constraints and allow fewer decisions and as a consequence simplify in a way the difficult task of image analysis.

The most obvious consequence of the decoupling philosophy described above is that systems have choked themselves on oversampled data. Resolution has to be determined by the finest feature to be identified. Thus regions which do not really have to be scanned at all are scanned, and are scanned at fine resolution. Only manual digitization avoids all this. The more subtle consequence is the loss of dynamic control over the sensing device, i.e. over thresholds. Single calibration of a sensor for an image of a varied scene can cause serious problems. Loss of contrast and corresponding requirements for digital enhancement are common.

The dynamic control of the sensing environment, i.e. position, resolution, and calibration, by an intelligent process offers the promise of a smaller volume of higher quality data and less execution cost. There is also the capability of viewing the same data in different ways by re-examining it in several stages of a feedback loop driven by the state of knowledge gathered about the data. Such a purposive system would have to contain a rich knowledge base to support its decision-making. Judging by the size of current geographic data bases amd encodings of application specific knowledge, the process that intelligently takes its input is likely to be choked with knowledge instead of data.

4. Components of the digital ACES

Section 2 defined the outputs desired from an ACES system and Section 3 described inputs available to ACES in order to arrive at the outputs. This section discusses components of ACES which must cooperate in this transformation of inputs to outputs. There is much to do since raw imagery is the basic input and symbolic graphics are the basic output.

4.1 The base map archive

It was emphasized in Section 3 that a rich knowledge base would be necessary for ACES to automatically extract features from raw aerial imagery. A geographic or cartographic data base could provide for a large portion of applicable knowledge, in particular specific locational knowledge of previously mapped features. Geographic data bases exist today and are proliferating. Current uses are not oriented toward guiding image analysis, so novel enhancements to current data bases should be expected to tailor them to the image analysis task. Ways of augmenting current data bases are discussed below.

For compactness and high symbolic representation, it seems best to archive (map) only the lineal and point features of the earth. Regions are defined by a lineal encoding of their boundaries. The basic element of the geographic data base is the lineal segment (edge) which is characterized by beginning point (xb,yb), ending point (xe,ye), and 3 feature codes FL,FO, and FR which specify the region feature to the left, the lineal feature itself, and the region to the right. Lineal segments intersect at points called nodes or vertices and the set of segments together with the set of vertices yield a graph which represents the topology of an area of the earth. This is the basic structure of the DIME file of the Bureau of the Census [Silver 1977]. To preserve geometric shape as well as topology each segment can be associated with a chain of points from (xb,yb) to (xe,ye) [Chrisman 1974]. This stored chain of points is not only of value in the plotting of a product but also is useful for identifying that boundary in new imagery of the same area. If the boundary segment is tagged as unique or special by either manual or automatic means, it may well be used for the initial registration of image to archive. While FO is a pointer to information about the shape and tone of a lineal feature, the pointers FL and FR can point to information identifying the content of the regions on either side. More than just a region number is appropriate: tonal signature could be specified by means of a discriminant function to be used for recognition of pixels in that region. With such stored information, the tracking of lineals in raw imagery could be guided by map content.

There will be problems in using a map archive to guide image interpretation. First of all the archive will be large and hence on external storage. Thus it will be necessary to stage processing so that symbolic archived information and raw sensed data arrive at the computer together. Secondly, it is desirable that the same map be applicable to the analysis of images of different scales and the generalization problem will be encountered. Generalization principles often require logical interpretation contrary to the physical facts depending on level of detail required. Such processes will be very difficult to do automatically. Third, the raw input will be in raster or array format while the archived data will be lineal (random) and symbolic. Due to the large amount of symbolic and raw data to be compared, both image and archive will need to be highly structured and compared in sorted order. This implies a great deal of processing overhead in searching and in I/O.

4.2 Class slice or thematic files

An ACES system would probably have to preprocess the raw aerial imagery to some extent in order to reduce the data volume and increase symbolic content. The most primitive operation in this direction would be to place symbolic labels on each pixel (x,y) of the image based on a vector $\bar{m}(x,y)$ of measurements taken over a small neighborhood of (x,y). $\bar{m}$ is easily conceived as a set of bands in the MSS case and could be combined tonal and textural measures in the B&W case.

To each pixel $(x,y,\bar{m}(x,y))$ of the preprocessed image can be assigned class labels from a pre-determined set $C = \{c_1,c_2, ,,,,c_k\}$. The label set is not mutually exclusive and the decision to label point (x,y) with label c_i could be independent of the decision to label (x,y) with c_j. In this manner k binary images $C_i = (x,y,b_i(x,y))$ could be generated from the preprocessed image independently and in parallel according to the decision rule

$$b_i(x,y) = 1 \text{ iff } P(c_i|\bar{m}(x,y)) \geq t$$

where $P(c_i|\bar{m}(x,y))$ is the probability that c_i is the class label given measurement vector $\bar{m}$ and t is some threshold. Binary images thus created are called "class slices" or "overlays". Note that the same position in several class slices can be 1, reflecting ambiguity or mixed properties of $(x,y,\bar{m}(x,y))$. Class slices could be used for extraction and separate processing of uniform map features such as road networks, vegetation, desert, etc. Each class slice can be further processed according to specific semantics without regard for the processing of other slices if appropriate. A very high level control can finally integrate all k class slices to form a consistently interpretable image.

Overlays formed in this manner can be cleaned up by operations discussed in Section 6 of this report or can be passed against the lineal feature archive for massaging or change detection. When cleaned the overlays can be plotted creating desired map products and can be processed for update of the lineal feature archive. Because of their large bulk and low level of symbolization, overlays probably will not be saved permanently after image analysis is complete.

4.3 Elevation matrices

The elevation of a point (x,y) may be received as one measurement $m(x,y)$ which cannot sensibly be reduced to a binary value. $m(x,y)$ is derived by using two (stereo) images not one. Elevation data must be viewed as a finished output product of ACES as well as a valuable input to aid in other image interpretation tasks. Elevation data for use by automatic procedures is probably best left in matrix rather than lineal contour form.

4.4 Procedural knowledge routines

Part of ACES a priori knowledge will be embedded in procedures or programs. Procedural knowledge is necessary in cases where the declarative knowledge, such as that stored as data in the map archive, is insufficient for decision making.

It is difficult to encode as data the rules of thumb that "roads tend to be continuous and tend to intersect other roads at blunt angles", yet it is not difficult to program such rules. Such a "road-knowledgeable" program is just what is required to clean up the road class-slice as discussed in 4.2. Such procedural knowledge is only applicable in specific contexts; while the aforementioned program might also do well on drainage features it would not apply to other overlays. Similar procedural knowledge is applicable to region type features. For example, "water tends to be continuous in 2-D extent at points with the same elevation".

4.5 Utility routines

A great deal of ACES system overhead can be expected in dealing with image data and in accessing the knowledge base and temporary overlay files. A large number of utility routines will be required in order to support ACES analysis. Once feasible decision-making algorithms are devised the special support hardware and software required will become evident and should be state-of-the-art.

4.6 Process control

The most complex part of ACES will be the control mechanism used to integrate the raw data and a priori knowledge in the interpretation decisions. Making decision with contradictory or ambiguous information is included in the task. Past A.I. work has developed several methods of control, all of which seem too weak and inflexible for attacking the image interpretation task at hand. These control methods include the following.

- finite automata
- semantic networks
- production language
- Bayesian inference
- theorem proving/predicate calculus
- hierarchical pattern classification

The first ACES systems will thus be controlled in a highly stereotyped or constrained manner, applying to the task only that fraction of applicable knowledge that is practical under current representational and decision making paradigns.

5. Knowledge available to ACES

It is now obvious to researchers that automation of areal image analysis will not be achieved unless large amounts of a priori real world knowledge is available to analysis procedures. This section surveys and categorizes knowledge sources which support the interpretation of spatial geographic imagery. It is easy to believe that humans use all of these knowledge sources, either consciously or unconsciously, in their image analysis tasks. Unfortunately, knowledge available to a human who may readily use it may be unuseable to a machine due to the practical problems of encoding it, accessing it and synthesizing complex decisions from that and other knowledge sources. "Knowledge engineering" [Feigenbaum 1977] is at an interesting stage of development but has not yet demonstrated the capability of handling general image analysis tasks. Not only is there a problem of combining knowledge in complex and possibly ambiguous situations but there is also the problem of efficiency in case a logical solution exists. Computers have neither the complex decision control strategies of the human nor the vast memory resource. It is therefore necessary at this point in time for scene analysis researchers to carefully select and define knowledge sources useful for implementation and to carefully test their performance capabilities.

5.1 Spectral or tonal knowledge

The reflectance from a particular material should remain relatively constant from one observation time to another when viewed with the same sensor. There will be some alterations due to changes in the atmosphere or sensor electronics or due to changes in the material itself such as maturing of foilage. Catalogues of signals can be compiled showing typical reflectances received by different sensors. With Landsat data each sensor samples a specific band of the electromagnetic spectrum. Use of several reflectances can usually narrow the classification of an unknown ground element to a few possible materials. Much cataloguing has already been done at the ERIM laboratory [ERIM 1975]. Vincent [1973] has presented a technique using the ratios of different spectra to achieve classification which is less sensitive to atmospheric and sensor changes than using absolute signal levels. Thus with MSS data, approximate pixel classification is easy to get in terms of theory and computation. Higher level knowledge is necessary in order to refine results of spectral classification. With black and white imagery (B&W) only shades of grey are available at the pixel level and thus little classification information is available from tone alone. Connected areas of pixels of the same tone can sometimes be amassed providing regions which can be classified according to their size and shape. This implies use of other types of knowledge.

5.2 Spatial, structural, or geometric knowledge

Most geographic entities are partly characterized by their 2-dimensional extent in the image. Features are usually continuous and large in size relative to the resolution elements. These assumptions allow the collection of similar pixels into contiguous regions or curves. Once regions or curves exist, geometric features can be used for classification.

5.2.1 Neighborhood dependence

Since observed regions are assumed to be large relative to pixel size, the probabalistic interpretation of adjacent pixels must be done jointly rather than independently. One way to do this is to allow the neighbors of a pixel to condition the probability of classifying a pixel in any primitive class. Another way would be to interpret the class of a pixel to be as the majority of preliminary classifications of neighbors without use of context.

5.2.2 Connectedness

Region or curve features are imaged onto connected sets of pixels. Connectivity may be violated due to noise especially in the case of curves. Tracking connected sets of pixels which have similar image features is an easy job for the computer because connectivity can be checked by only local operations. Tracking of connected objects can also be adjusted to allow for some noise distortions.

5.2.3 Shape and size

Once regions and curves of connected sets of pixels having homogeneous properties are assembled, these objects can be interpreted by size and shape features. (Many size and shape features can be computed while the connected objects are being tracked. See [Agrawala 1977]). Thin smoothly curving objects are likely to be streams or roads according to a real world model. Long, thin, straight objects are almost surely roads. Large rectangular objects are likely to be housing blocks or agricultural fields.

5.3 Spatial distribution

Often the interpretation of an object will depend upon how it relates to other objects in its proximity. This neighborhood dependence is more general and higher level than that discussed in 5.2.1. If several poloygonal objects of a certain size are detected in close proximity to each other, the entire set may be interpreted as buildings. Nearby road features would further support such an interpretation.

5.4 Associative/semantic knowledge

Perhaps at the highest level is associative or semantic type knowledge which allows image features and objects to be interpreted or understood with respect to a global model which is causal or relational in nature. This requires detailed understanding of the functions or purposes of objects and relationships among them which are not apparent in the imagery. For example, we have the general knowledge chunk "evergreens grow on steep rocky slopes". This knowledge relates geological structure and elevation information to vegetation type and might be particularly useful in the interpretation of B&W imagery where all three related items -- evergreens, rocks, and steep terrain -- could not be simultaneously observed. A second example is the knowledge that "drainage matches terrain". The causal model is that water runs downhill only and its passage erodes the ground. This implies that an observed stream path must always follow a non-increasing sequence of elevations and that elevations on the path are likely to be lower than those at right angles off the path. This type of model can be made "known" to an automatic device by encoding it into a tracking procedure specific to drainage features. Since roads can travel up and down hills, the same knowledge is inappropriate for tracking roads. A third example giving knowledge useful in detecting roads is that "roads often have long straight segments and tend to intersect each other". The appropriate model is that roads are man-made and connected into a network to allow traffic between many points. In the absence of obstacles or varying terrain the most efficient path is along a straight line. Such knowledge can be used by an automatic system in the following manner. At a low-level of the system edge features can be aggregated to form curves. Any curves of certain dimensions which have straight segments would strongly imply a road feature. At the next level of the system the topological relationship of connection would be observed. Any connection of degree 3 or 4 of two curves, each having a straight segment, would further support the road interpretation. Gaps in curves of an assembled network could be checked more carefully for edge content and for geometrical alignment and the gap filled if appropriate results are obtained.

5.5 A priori positional knowledge

The most specific, and perhaps the most useful knowledge to an automatic system, is positional knowledge of features as stored in a geographic data base (GDB). The points along linear features recorded in the data base are easily used for interpreting imagery registered to the data base. For instance, the forks of the Shenandoah River at Front Royal would certainly be encoded in a GDB of that area and would be readily used in interpreting the drainage versus road network in imagery of the area. Encoded road features, on the other hand, would be useful in tracking the full road network after initial registration with points of the image. The continuity of the iconic features in the GDB would be invaluable in efforts to overcome the fragmenting effects of shadows, poor contrast, or vegetation canopy. Presence of roads would lend power to the interpretation of building-like objects detected in the imagery but not present in the GDB. Presence of streams would aid in the search for new bridges and hence new roads.

A priori knowledge need not consist of only iconic or geometric feature type knowledge but can also be very general. For instance, given imagery over the state of Maryland, it is known that there will be no glaciers and no large lakes. This knowledge may enable the isolation of large areas of cloud cover in the imagery. Together with the known time of the imagery it could also be known exactly which land classes would be present for interpretation. For example, for March imagery over Garret County, Maryland snow cover would be highly likely while vegetation would be much suppressed. With MSS data, classifiers (class-slices) for snow and conifer could be used but classifiers for corn or tobacco could not be used.

5.6 *Use and encoding of knowledge*

The previous sections discussed various categories of knowledge available in image interpretation and gave some specific examples. It is appropriate to examine in more detail exactly how such knowledge can be encoded and used for automatic interpretation. Knowledge can be encoded in a <u>declarative</u> form, meaning that it is encoded as data to be used by a uniform decision procedure. A <u>uniform</u> procedure is one that behaves the same way for all feature classes. Spectral knowledge is easily encoded in this form -- discriminant functions (specified by coefficients) or signature prototypes can be used to define classes of data and the same decision procedure can be applied for all classes of data. Knowledge can also be encoded in <u>procedural</u> form, meaning a program is written to implement the knowledge. Very high level feature specific knowledge is perhaps best implemented in procedural form. Declarative and procedural implementations each have their respective advantages and disadvantages -- for an interesting discussion see [Winston 1977]. Table 5.1 relates the several knowledge sources previously discussed to methods of encoding and using that knowledge in a computer.

Table 5.1 Encoding and using knowledge

Category of knowledge	Encoding of knowledge	Use in interpretation
Spectral/tonal	(declarative) prototypes, discriminant functions, density functions	use to classify single pixels by estimating p(given class|spectral info.)
Spatial/neighborhood	(declarative) extend above to work on joint information	use to classify single pixels by p(given class|spectral info. of neighborhood)
	(procedural) use connectiveness property in tracking procedures	use to asemble larger objects such as regions and curves
Spatial/geometric	(declarative) set of possible labeled features each with list of qualifying properties	uniform procedure assigns labels to image objects by checking properties
	(procedural) set of possible labeled features each with qualifying procedural logic	key properties causes control mechanism to evoke specific procedure to recognize specific feature from properties
Spatial distribution	(declarative) syntactic approach possible but not recommended (procedural) set of procedures for interpreting cartographic features, one procedure for each feature	interpret individual objects by considering a set of objects and their properties in an attempt to assign consistent interpretations to all according to spatial relationships
Associative/semantic	(declarative) syntactic or deductive approaches possible but not recommended (procedural) set of procedures for interpreting cartographic features, one procedure for each feature or group of associated features	use to clean up networks of curves and regions. Use to perform top-down search for faint features connecting to a network or faint features enclosed in regions. Perform more specific interpretations of objects according to arbitrary combinations of current information.

5.7 Discussion of knowledge sources useful for ACES

Several of the knowledge sources described above can readily be applied to automatic image interpretation while several seem unuseable given the current state of the art. Spectral or tonal information is easily and efficiently applied. The assumption is that the material content of an element of the earth's surface is easily classified from the spectral characteristics of its reflectance. Spectral, or MSS, classification is in fact computationally easy as is evidenced by the plethora of implementations and experiments reported. Classification performance has not always been satisfactory, however, largely because of the "signature extension" problem - - that of classifying data gathered under circumstances different from those existing for training. The beauty of MSS classification is that it interprets geographic image data at the lowest level without any spatial context or complexity of decision. When viewed as a final process, MSS classification is error-prone and insufficient for structural interpretation of an image; when viewed as a low-level data interpretation and reduction step, MSS classification could be regarded as a necessary and valuable step in image analysis.

Properties such as connectedness or adjacency are also easily handled by a computer because of local operation. Decisions made at a point in the space depend only on very limited context around that point. If natural geographic regions in fact image to many resolution elements it is clear that limited context decisions can significantly improve the performance of interpretation [Welch 1971].

Spatial texture features are more difficult to apply because there is no uniform neighborhood over which to compute them. Gramenopoulos [1973] and Haralick [1973] have reported good results with texture features computed over fixed windows for land use classification. However, caution must be used in evaluation of these results because the mathematical models used to capture texture seem very weak when compared to human perception of texture in analysis of black and white photography. Black and white photography appears to be particularly unsuited for automatic feature extraction because of this dependence on texture perception over variable-sized regions and almost complete unavailability of tonal cues.

Associative/semantic type knowledge is also difficult to apply in automatic processing because of many factors: 1) it tends to be highly specific, 2) it is difficult to determine exactly which contexts ellicit its use, and 3) the output product of using the knowledge is hard to define in terms of inputs. Consider these points in application of the knowledge that "drainage matches elevations". Unfortunately definitive use of this "matching" would probably result in a procedural implementation of the knowledge as discussed in Section 5.6.

Primitive shape and size features are very important for automatic processing because they are easy to extract and should be more reliable interpretive cues than single tonal samples. The aggregation of similar tones or gradient into straight or highly curving arcs, for example, can significantly reduce the effects of noise, yield higher level interpretation, and enable registration with structures in an existing map. Knowledge of shape alone is insufficient to distinguish between a road and a river and it is clear that other knowledge must be invoked to make a distinction. At the lower end, spectral information and knowledge would easily do the job and at the higher end "matching" with elevation information could do it, but with somewhat more calculation.

Although very specific, a priori positional knowledge is easy to use and will be invaluable in automatic image analysis. A priori positional knowledge is already used in semiautomatic systems to establish the registration of image points to points in a standard coordinate system. With registration, base maps become highly organized knowledge sources useful for the interpretation of new imagery. The base map could be regarded as an organized summary of the previous analysis of the same area. Registration allows previous interpretation, whether human or automatic, to guide future interpretation. There are many specific techniques to consider; such as verifying the presence of bridges over drainage or scanning known parking lots to count vehicles. It is vital to recognize the general importance of the role of registration in applying existing knowledge stored in a geographic information system. Some general capabilities are as follows.

1) For assessment of change significant features of an image must be compared with significant features of a map. Identical features should of course correspond positionally via registration. Significant features are those detected after some structural combination of tonal elements.

2) For calibration of the sensor it might be necessary to compare regions of the sensed data with known regions in the data base. As an example consider the case where a lake is known to exist in the area. After registration, tonal samples could be taken from the image in a region known to be lake. The calibrated water signal could then be used to detect other water bodies in the image.

3) For multidate feature extraction, registration is absolutely essential. By correlation of positions in images taken during different seasons, greater information should result as opposed to single date imagery. In this way, for example, deciduous and coniferous forest might easily be distinguished, from each other and from other land classes.

6. Automatic recognition of features

Aerial imagery has been used as input to map compilation since before the advent of the airplane. It has been estimated that perhaps 80% of all map features can be extracted from photographs (Doyle, 1973). Cartographic features can thus be put in 3 categories-- 1) *features that are not apparent in* aerial imagery, 2) features that are apparent in aerial imagery but cannot be easily extracted automatically, and 3) features which can be easily extracted from aerial imagery. Existence of category 1 precludes <u>complete</u> automation of <u>complete</u> maps. However, accommodation for category 1 by any semi-automatic system easily provides a way out for category 2 problems. The relative size of category 3 is not known. Experiments in automatic image interpretation are continuing to make progress. One of the greatest stumbling blocks to this progress is the lack of available data at the resolution necessary to classify features. For example, researchers (Li, 1976; Bajcsy, 1976; VanderBrug, 1976) have been struggling with the mapping of roads using the insufficient ground resolution of ERTS imagery.

Cartographic features which are certainly not available from aerial imagery include political boundaries, place names, building functions (i.e. church, general's headquarters, etc.), past features (i.e. a forest removed 2 years ago), and subsurface features (i.e. rock formations, mines, pipelines). If desired on a map these features must be gathered by other collection techniques and positionally merged with features extracted from imagery. Cartographic features which are apparent in imagery and might be extracted automatically include elevation data, soil regions, vegetation regions, urban regions, water bodies, water networks, and road networks. Further breakdown of these classes is possible. For example, vegetation regions include forest, crop, scrub, and park. Further discussion of map feature classification is reserved for the next section.

If there is a 1 to 1 correspondence between ground resolution elements and map resolution elements, a thematic map can be produced by simply printing the map element in a color (theme) coding the land class of the ground resolution element. For example, resolution elements inside a lake can map into blue squares on the map, elements inside a forest can map into green squares, etc. The color code need not be natural--roads could be red for instance! The color code for the land element is chosen by classification logic acting on the spectral signature of the ground resolution element. While no human would be so foolish as to do this, an automatic device is likely to require and succeed at such a simple 1 to 1 coding of an image. The machine has decided advantages over the human in spectral and multispectral classification in the absence of spatial information. A map produced by a 1 to 1 coding of resolution elements will be called a thematic map. Thematic maps have been produced for several years from ERTS imagery. They can be regarded not only as finished products but also as input to further map compilation. Although often quite rough when created as described above, thematic maps are quite useful for human consumption because the hum interpreter can smooth and adjust the results during his interpretation. Additional processing is necessary to convert thematic maps to symbolic maps meeting cartographic standards. Further processing of thematic maps is covered in section 6.4.

When we speak of the automatic recognition of "cartographic features" we are refering to features symbolized on a map such as roads and streams. In order to automatically extract cartographic features from aerial imagery algorithms must ultimately measure "image features" which may be quite diferent from cartographic features. Traditionally, image features have been measured for each pixel (x,y) during preprocessing. What image features are available certainly depends upon whether there is single sensor or MSS data. With MSS data there are several registered tonal samples for each pixel; often enough to yield image features meaningful for compilation of cartographic features. Besides tonal measurements on (x,y) there are measurements which relate to the texture or 2-D structure of a local neighborhood of (x,y).

Together the tonal, structural, and textural measurements at (x,y) could be used to include (x,y) as a point in some cartographic feature. Use of MSS imagery for automatic cartographic compilation is treated in Section 6.3. The case of B&W imagery is taken up in 6.4.

6.1 Classes of data

Interesting classes to be coded on a map were discussed above and include soil, vegetation, water, etc. There are problems with land classification which do not become clear until automatic classification is considered. There is no worldwide standard for soil classification (McRae, 1976) and vegetation classification: therefore, general a priori catalogues of map features are of dubious value and intent. Moreover, map makers have relied on tradition and subjective judgment in their mapping. Two points become critical when automatic mapping is considered. First of all, objective criteria must be used for land classification. Difficulty in matching objective criteria of a machine to subjective criteria of humans using its product is evident from the confusion matrices gotten in land use classification experiments. Secondly, if we are really interested in (fast, economical, effortless) automatic classification it may be necessary to choose the classes in order to optimize the machine's performance. This could mean using a posteriori labels, i.e. clustering, and making the human consumer adapt himself to the product, or using a priori labels, but only for a class hierarchy that is known to be separable. Some major classes are easily distinguished, i.e. bodies of water in the infrared band, but fine subdivision can be difficult, such as distinguishing among 10 different crops.

Past research seems to indicate that successful thematic

mapping can be achieved with the 4 classes of urban, bare soil, water, and vegetation (Gramenopoulos, 1973) and that up to 20 different classes may be practical (Anderson, 1971).
Note that 20 different classes in a thematic map could yield many more, and perhaps an acceptable number of, symbolic map classes. This is because several classes of the same road theme could be separated by size, rivers could be separated from lakes, forests from parks, etc. In addition, spatial compositions of the primitive themes could yield unique map symbology, i.e. a pattern of buildings, roads, and trees could yield a region symbolizing a town. Table 6.1 gives a list of thematic classes for which we might have some hope of successful separation and table 6.3 gives a list of map symbols derivable from them. It must be emphasized that tables 6.1 and 6.2 represent preliminary suggestions and not final conclusions.

With MSS data primitives themes are used to classify resolution sized pixels only. Only the signature of the pixel itself or the signatures of immediate neighbors will be used to make the classification decision. Spatial structure, shape, or texture therefore cannot be used as features for classifying single pixels. There has been some problem with this in the past, largely because ERTS resolution elements are about an acre in size and could easily contain several primitive land classification themes as given in table 6.1. Ground resolution and map symbology must be appropriately matched. For recognition of roads a ground resolution of 10 m or better is necessary. At this resolution "lake" or "forest" cannot be used as primitive themes. In order to recognize a forest a large extent of tree pixels would have to be first recognized. Aggregation of primitive themes into regional units of information is a major function of map making. Curves of asphalt or concrete pixels need to be collected in order to recognize and symbolize a road. When the map is printed or stored, for most map scales, trees lining the mid strip of a divided highway will be suppressed rather than symbolized. Similarly, a small pond within a forest, even if several pixels in extent, might be suppressed.

Table 6.2 gives some of the knowledge sources that are useful in interpreting arrays of thematically classified pixels for producing map symbology. Table 6.3 contains map symbology that may be inferred from aggregation or composition of primitive themes (table 6.1) using the knowledge sources (table 6.2). Table 6.4 gives an example of primitive themes and map symbology that might be useful in compilation of 1:100,000 maps of Maryland. Roads and drains are gotten by 1-D aggregation of appropriate primitive theme pixels. Lakes and forests are gotten by 2-D aggregation of regions of uniform themes. Other map regions must be gotten by extension of dissimilar themes. For example an urban region is composed of appropriately textured or distributed pixels of all primitive themes while a swamp is a region textured appropriately with water and vegetation themes. Higher level processing of thematic information is treated in section 6.3.3.

Table 6.1 Thematic Classes

Primitive Themes	Possible Subthemes
1. Water	
	1.1 Cloud
	1.2 Snow or ice
	1.3 Liquid
2. Bare Rock or Soil	
	2.1 Sandstone
	2.2 Salt
	2.3 Granite
	2.4 Limestone
	2.5 Loam
	...
3. Vegetation	
	3.1 Tree
	3.1.1 Deciduous
	3.1.2 Conifer
	3.2 Bush
	3.3 Groundcover
	3.3.1 Grass
	3.3.2 Wheat
	...
4. Man-Fabricated Material	
	4.1 Asphalt
	4.2 Metal
	4.3 Concrete
	4.4 Wood
5. Elevation	

Table 6.2

<u>Knowledge Sources</u>

1. Spatial

   1.1 neighborhood
   1.2 statistical co-occurrence
   1.3 texture

2. Structural

   2.1 connectivity
   2.2 shape
   2.3 continuity

3. Semantic

   3.1 drainage matches elevations
   3.2 streets tend to be perpendicular
   ...

4. Climatic

   4.1 time of year
   4.2 precipitation
   4.3 temperature

5. Positional

   5.1 previous maps
   5.2 specific regional information

Table 6.3 Map Symbology

Aggregations of Primitive Themes

Water	
Cloud	(T1.1)
Snow or ice	(T1.2*&(K4,K5)**
Drainage	(T1.3)&(K2,K3,K4,K5)
Storage body	(T1.3)&(K2,K3,K4,K5)
Intermittent drainage	(T1.3)&(K2,K3,K4,K5)
Forest	(T3.1)&(K2,K3,K5)
Cropland	(T3.3)&(K2,K3,K5)
Elevation	(T5)&(K2)
Roads & RRs	(T4.1,T4.3,T2)&(K2,K3,K5)
Building	(T4)&(K1,K2,K3,K5)

Compositions of Primitive Themes

Urban	(T1-5)&(K1-5)
Residential	
Industrial	
Swamp	(T1.3,T3)&(K1,K3,K5)
Desert	(T3.2,T2)&(K1,K3,K5)
Savannah	(T3)&(K1,K3,K5)
Alpine	(T3,T5)&(K4,K5)
Beach	(T1,T2)&(K3,K5)

* T refers to "primitive theme" as in table 6.1

** K refers to "knowledge source" as in table 6.2

6.2 Available sensors

Any emittance or reflectance from the earth that is transmitted faithfully through the atmosphere can be used for remote sensing of the earth's properties. Electromagnetic radiation with wavelength range of 0.3 microns (μ) to 3 cm is practical. This includes near ultraviolet, visible light, infrared, radar and microwave. Generally resolving power decreases with increasing wavelength but effectiveness in fog or cloud cover increases. There is no best sensor for all recognition tasks and all resolutions. ERTS-1 sampled four bands of the spectrum from 0.5μ to 1.1μ with a coarse ground resolution of about 70 m. (See **Estes**, 1974.) ERTS-2 has 2 added bands, one on each end of the set of bands sampled by ERTS-1. Scanners and photographic equipment collecting sunlight reflected from the earth or thermal radiation emitted are called <u>passive sensors</u>. <u>Active sensors</u> include radar and lasers. Low altitude active night photography can also be done. Unclassified radar systems have a ground resolution capability of 10 m (See **Estes**, 1974.), well within the range needed for useful cartography. Resolution for the visible bands of the spectrum range from 1 m to 1000 m depending on altitude and purpose of collection.

Table 6.5 summarizes the capabilities of some sensors for use in classification of land features. In some cases only one band is necessary for good detection. Water, for instance, is readily detected in the infrared band. Radar or visible color information can augment the infrared information if needed. Different kinds of information are gotten about vegetation from the different bands (**Estes**, 1974). Variations in pigmentation is gotten from the visible, structural differences in spongy mesophyll are seen in the near infrared, and moisture stress is picked up in the far infrared. More progress in sensor technology is expected and research in classification is continuing. Progress is needed in order to transfer classification successes over temporal and locational changes of data collection.

Table 6.4

Example for 1:100,000 Map Compilation

in Maryland Region (R_g = 5m)

Primitive Themes	Map Symbology
1. Cloud	1. Perennial drainage
2. Snow or Ice	2. Water bodies
3. Liquid Water	3. Forest
	4. Swamp
4. Sand	5. Beach
5. Other Exposed Earth	6. Elevation contours
	7. Roads
6. Tree	8. Railroads
7. Brush, Crop, Groundcover	9. Urban, small
	10. Urban
8. Asphalt	11. Urban, extensive
9. Concrete	

Table 6.5

Sensors for Detection of Primitive Themes

Primitive Theme	Sensor
Water	infrared, radar
Bare rock or soil	visible color (Rib, 1973) night infrared spectral ratios (Vincent, 1973)
Vegetation	visible color infrared (Estes, 1974)
Man-fabricated material	visible color infrared radar
Elevation	visible stereo pairs

6.3 Recognition of cartographic features using MSS data

The chief advantage of MSS data over single sensor data is that a large amount of information is available in tonal image features at each point (x,y) and thus ground element classifications can be made in a logically and computationally simple manner. Class-slices, or overlays, gotten by low level pixel classification was discussed in Section 4.2. The result is that binary images $(x,y,b_i(x,y))$ can easily be created for any primitive cartographic feature c_i. The set of all such class slices thus created would define a crude thematic map.

There are at least 4 steps of refinement necessary in creating an acceptable cartographic product from a set of primitive class slices. First, very general "smoothing" operations, such as hole-filling and noise suppression should be performed on all class-slices independently. Secondly, feature specific processing algorithms should be applied to individual class slices. This could include comparison of the data with lineal archive data. Third, combinations of class slices should be considered simultaneously for creation of composite features from primitive ones and for adjustment of one feature due to the presence of another. Fourth, class slice data should undergo a representation transformation from array form to lineal form. This step might at first appear to be unnecessary if raster output is to be done. However, symbolization is inherent in the conversion from array to lineal representation. Lines must be thinned to centerlines and region boundaries must be tracked. As part of the symbolization process, lines on the map will be uniform in width and will be wider than life on small scale maps. These four steps in processing MSS data for cartographic feature extraction are discussed in more detail in the following sections. An overall view of the processing is given in Figure 6.1.

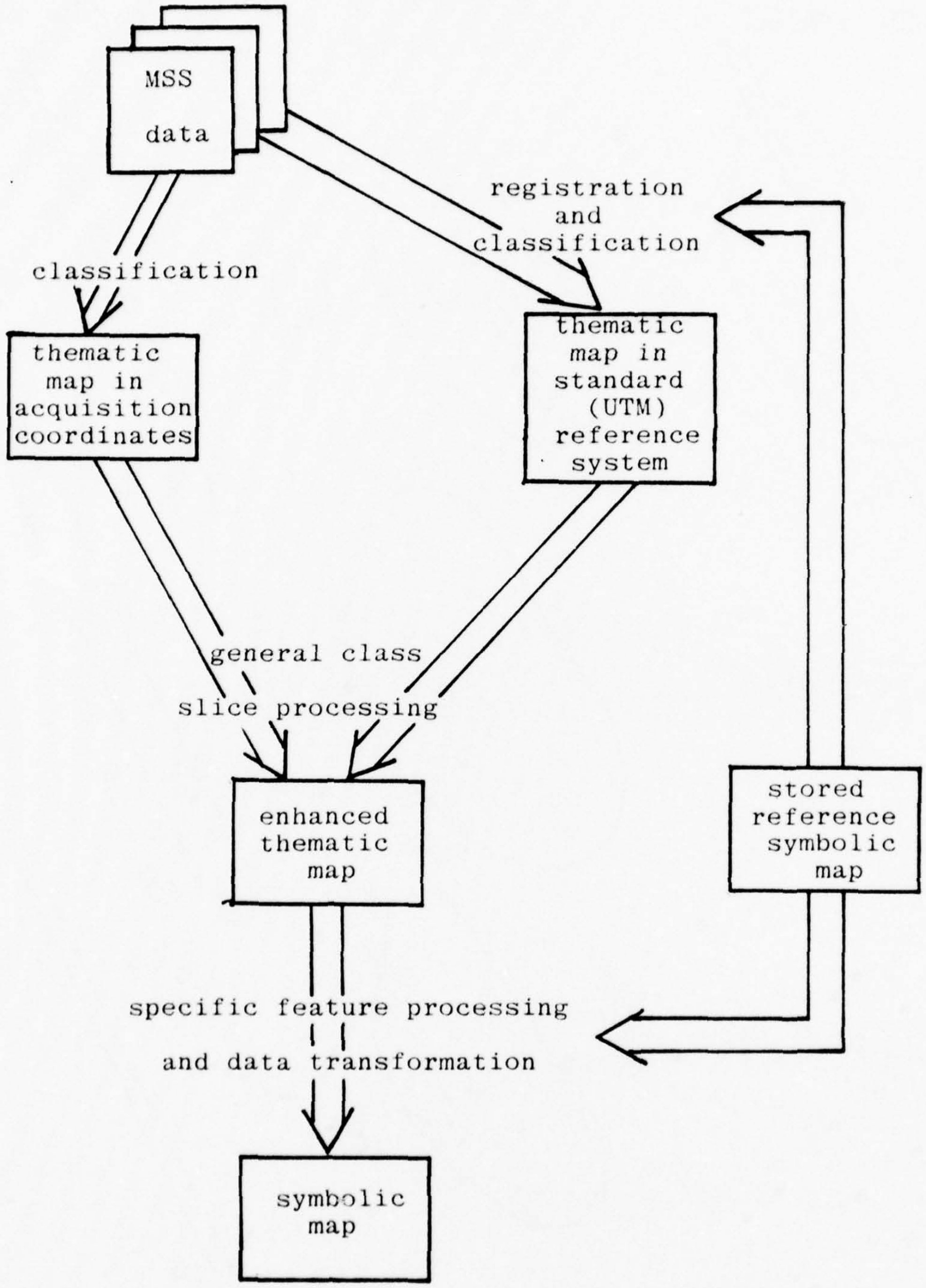

Figure 6.1 Possible steps for production of topographic maps from MSS data.

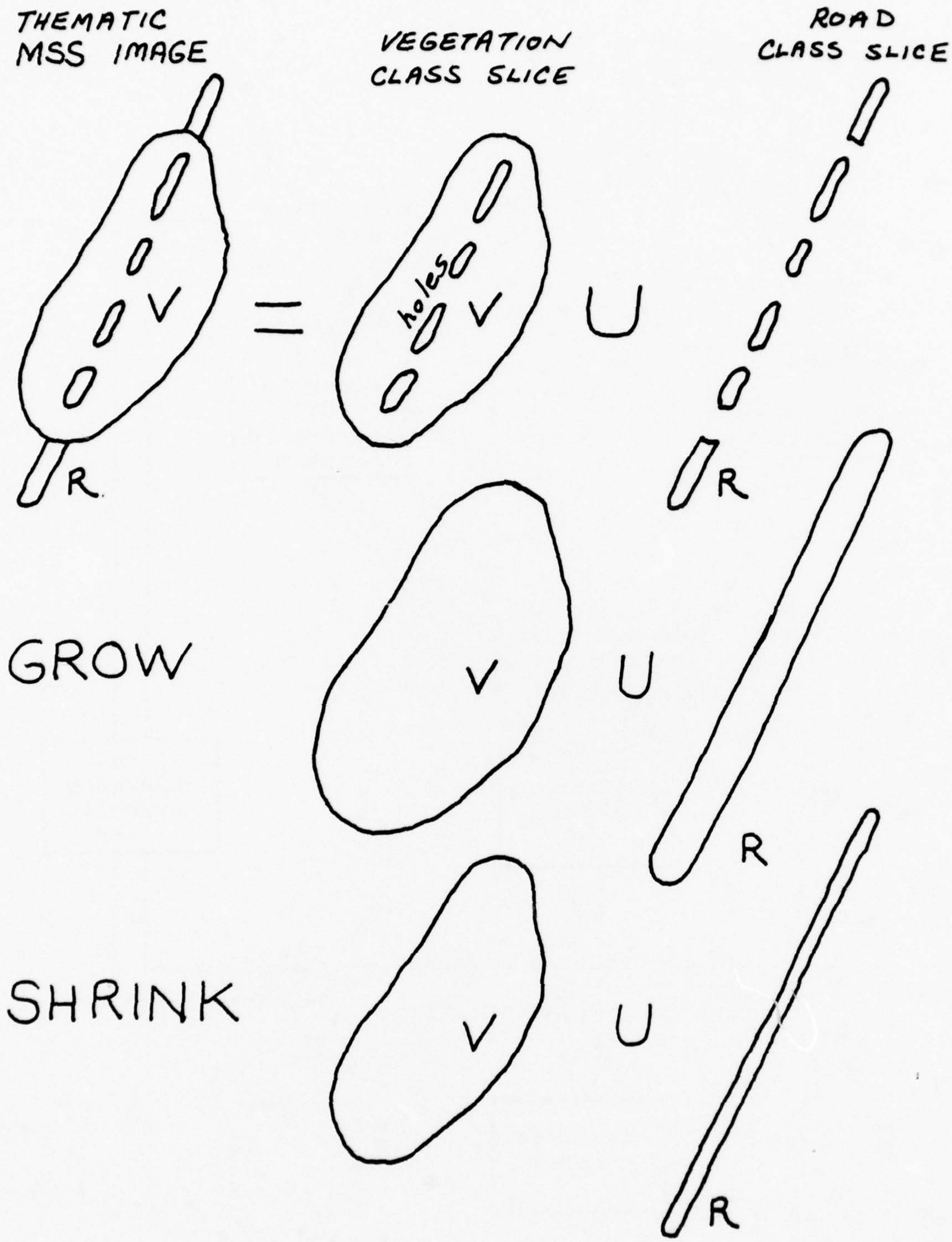

Figure 6.2 Filling holes and gaps by growing and shrinking

6.3.1 Enhancing thematic maps

Maps for human consumption require resolution which varies according to the features symbolized. For example, a forest feature need not be displayed with the same accuracy necessary for a road or building. However, a practical MSS scanning system will produce resolution elements of the same size for all features. In order to correct errors and suppress detail thematic maps need enhancements.

For logical simplicity it is assumed at this point that a separate (binary) image is available for each primitive theme classified. This will be called a class slice. By allowing several class slices we allow a given map resolution element to be associated with multiple themes. This not only simplifies processing but also aids in decision making and in fact corresponds to overlay formation in current automatic cartographic techniques.

Figure 6.2 shows how gaps and holes can be filled by a single simple process acting on each individual overlay. The particular example shows how continuous road features and solid vegetation regions can be assembled using a growing operation followed by a shrinking operation. Because the scanner partitions its window into ground resolution elements and because the classification logic is unlikely to identify two themes for the same pixel, road pixels will form holes in forest regions and forest canopy pixels will cause gaps in road themes. By

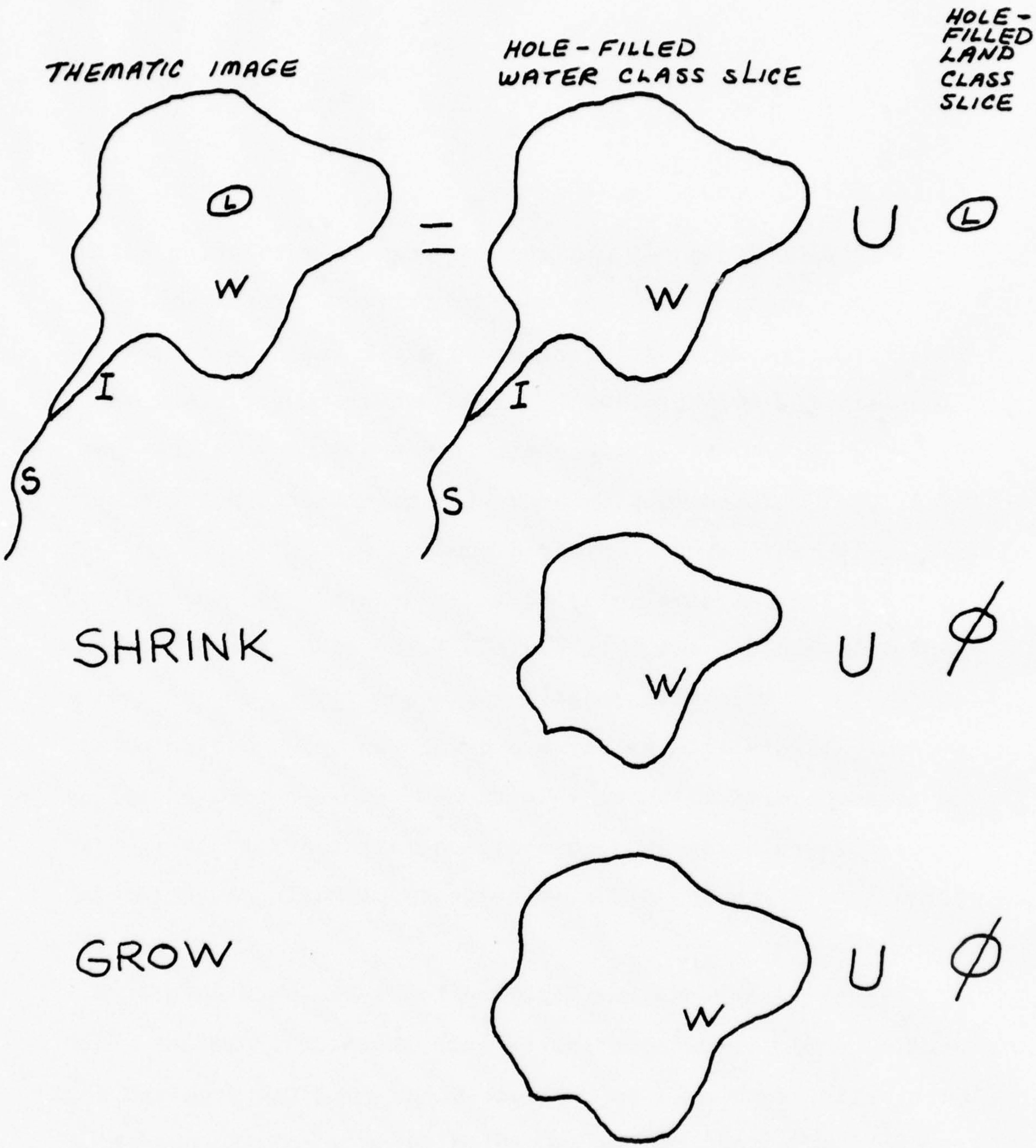

Figure 6.3 Suppression of isolated themes by shrinking and growing

growing the road class slice, segments of the road will fuse over the gaps and by growing the vegetation region the holes caused by the road will be filled. Shrinkage of the same amount would then return the vegetation area to its original form without the holes and would produce a continuous road of the same width as before but without gaps. The amount of hole and gap filling performed is controlled by a growth/shrinkage parameter. Results are not likely to be perfect but should definitely enhance the original class slices.

Suppression of isolated detail can be done by first shrinking and then growing as shown in figure 6.3. Isolated regions of a class slice which are smaller than the shrinkage parameter will disappear and thus not be restored by the subsequent growing operation. On the other hand, regions of a class slice of diameter larger than the shrinkage parameter will be restored to a "smoothed" version of the original. Note that the narrow inlet I in figure 6.3 will shrink away and not be restored. Class slices of gross areal features, such as water bodies and forests, will be enhanced by such processing, but class slices of lineal features such as road networks should not be processed in this way.

As a by-product of growing followed by shrinking, areas "peppered" with pixels of one class will fuse if the individual pixels are within a certain distance of each other. Because of this, swamp areas which are textured with water and

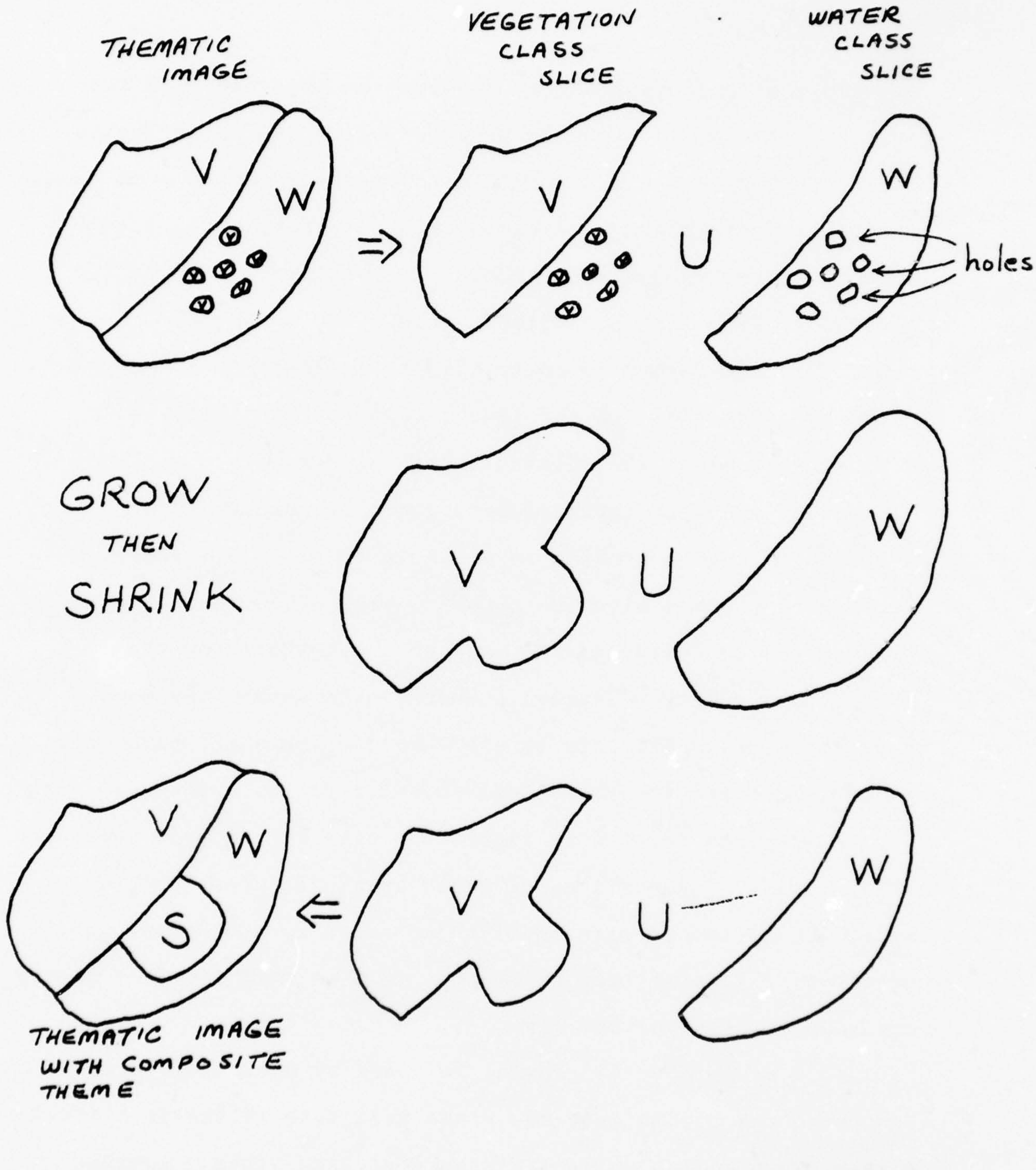

Figure 6.4 Overlapping regions caused by growing and shrinking yield textured regions defining composite themes. For example a swamp is a region textured with water and vegetation themes.

vegetation elements will be indicated by an area of overlap in the vegetation and water overlays. The swamp is termed a <u>composite theme</u> and can be detected as shown in figure 6.4 by intersecting the enhanced water and vegetation class slices. Other composites are possible; for example, a residential area could be defined by the intersection of asphalt and vegetation class slices.

6.3.2 Extraction of hydrologic features

Large water bodies can be gotten by shrinking and growing from the water class slice. The shrinking must be enough to suppress all small drainage features. A drainage class slice can then be created by logically subtracting the water body class slice from the water class slice. The drainage class slice could be partitioned into slices for large and small features by the same technique if required.

For compact storage or display by random point plotting, the boundaries of connected regions of the water body class slice could be tracked and chain-encoded (Freeman, 1961). Line-tracking algorithms could form a chain-encoded drainage network from the drainage class slice, possibly after a thinning algorithm is first applied to the binary image. The tracking algorithm could use heuristics to fill network gaps or could consult a map data base when making extensions of lines beyond the MSS evidence recorded in the class slice. For instance, a stream that is lost in foliage might be tracked by registering with a symbolic map created from winter imagery or by globally considering the drainage class slice and elevation matrix.

6.3.3 Roads and urban areas

Roads and urban areas can be handled in the same manner as drainage and water bodies. If the imagery is of high enough quality, separation according to road size may be possible (Radosevic, 1976). After or during tracking, the road network would need to be cleaned up by assuming continuity of single roads, intersections of nearby roads, and agreement with past mapping. Urban areas can be encoded by tracking the boundary of the urban class slice.

6.3.4 First level symbolic map

By tracking line networks and region boundaries the thematic map information becomes more highly structured--individual pixels, previously processed locally in parallel, are now highly related. The regions and networks thus formed are the basis for symbolic map production. Without further cleanup these features could be plotted to yield a first level symbolic map. Further map revision is discussed in sections 6.5 and 6.6 below.

6.4 Recognition of cartographic features using black and white imagery

Even with an array of tonal samples for each pixel it will be some time before processing steps as discussed in Section 6.3 could be made viable. In this section the possibility of doing automatic analysis with even less input data is examined. Cartographers and photo interpreters have been working with black and white aerial photography for decades. Such imagery is readily available and shows fine detail. However, in order to interpret B&W imagery, image features of a global scale must be used at primitive stages of decision-making. Humans readily use the Gestalt, or global character of a scene to make unambiguous local interpretations. Reproducing such a capability in a machine will not be easy.

As an example of the difficulty for automatic analysis of B&W imagery, consider the case of interpreting a dark area in an image taken near the Washington monument. The tone of pixels could indicate either water or asphalt leading to possible interpretations of either pond or parking lot for the entire dark area. Since both of these features could also have similar textures, it is impossible to differentiate locally from image pixel features. Even the shape of the feature is insufficient for discrimination; i.e. the reflecting pool is rectangular as a parking lot would appear to be. In many cases the context of neighboring features would be useful, but in this case the many concrete paths leading to the reflecting pool would support the parking lot interpretation more than the pond interpretation.

Although not all cases are as subtle as the case described above, there are many severe problems in using B&W imagery in automatic analysis. Distinguishing between roads and streams presents another difficult situation: tone, size, shape, and topological features may all be similar. The large amount of real-world knowledge possessed by trained photo interpreters allow them to rapidly arrive at globally correct interpretations even in areas for which they have no reference map. There appear to be two viable approaches to the automatic interpretation of B&W imagery. The first approach would use general contextual and relational knowledge to arrive at a unique consistent labeling of a scene given an ambiguous <u>set</u> of possible labels for each scene region or line feature. This approach is studied in Section 6.4.1. A far different approach to the problem is to do all analysis with respect to a base map of features in the area being image. Map-directed image analysis is treated in 6.4.2.

6.4.1 Arriving at global interpretation by propagation of local constraints

In this section the technique of relaxation or relaxation labeling is considered for use in interpreting the content of imagery. Currently a rage in image processing, relaxation was recently invented by Waltz [1975] and further developed by many others. The treatment rendered here owes much to Tenenbaum and Barrow [1976] who have applied relaxation labelling to image analysis problems with goals similar to those of this study.

Relaxation is basically a bottom-up process which filters through multiple possibilities allowed by the extraction of local information. Possibilities are thrown out rather than brought up as the propagation process drives toward a global interpretation composed of locally consistent parts. To start the procedure it is assumed that preprocessing has been used to extract lineal and region type objects from an image. The objective of the procedure is to discover the correct feature or label to assign to each object in the segmented image. For instance, each lineal object should be identified as a stream, road, or railroad while each region should be identified as urban, open water, forest, etc. Real world knowledge will be applied to identification of single objects by using features such as size and shape and to identification of sets of objects by considering spatial and topological relationships. Encoding real world constraints for use by a uniform procedure is one of the chief problems and is considered below. Getting the good segmentation of an image that we have assumed available is also a difficult problem and will not be further discussed here. (Zucker [197 and others have used relaxation at a lower level to extract the objects themselves.)

A simple example of image interpretation is developed in Figure 6.5 a-f. Possible labels (cartographic features) for region and lineal objects are specified to the process. These labels will be multiply assigned to each image object according to primitive measurements made during extraction of the objects. For instance a long thin curve may be labeled {R,RR,S} meaning that from information gathered so far this object may be either a road, railroad, or stream. If it is later found that this object connects to an object known to be a body of open water then the labels {R,RR} are discarded and the long, thin, curve is known to be a stream {S}. This interpretation might then be further propagated to refine the interpretation on other nearby or connecting objects. Six sample cartographic features are given in Figure 6.5a and four sample topological relationships that might exist between such features are defined in Figure 6.5b. Figure 6.5c gives sample real-world constraints on the cartographic features. For example, streams can connect to other streams, $\exists S_1 S_2 \ni c(S_1,S_2)$, but streams cannot penetrate other streams, $\nexists S_1,S_2 \ni p(S_1,S_2)$. Similarly the encoded constraints also state that roads do not connect to open water and that urban regions do not appear inside of other urban regions.

Figure 6.5d shows a sample image segmented into 4 lineal objects and 4 regions. The relationships known from the extraction process are given in Figure 6.5e. All that is known about the objects are the <u>observed</u> relationships and measurements, and that they must as a set satisfy the <u>a priori</u> constraints given in Figure 6.5c. We suppose that in this case enough information exists to know that region R1 is water W. The initial state of labels on the eight image objects is given in Column 2 of Figure 6.5f. Seven of the eight objects present maximum ambiguity. During relaxation, the facts of 6.5e are passed against the constraints of 6.5c to refine the sets of possible labels. For example, since water cannot be penetrated, i.e. $\nexists X \ni p(X,W)$, and R3 and R4 are penetrated by L1, then R3 and R4 cannot be water. Since L3 cannot be a road R or railroad RR t must be a stream S. Further propagation results in the final column of Figure 6.5f. A few ambiguities persist and cannot be removed without more knowledge. The paper by Tenenbaum [1976] should be consulted for more details.

While procedures such as that described above are promising and are the subject of much current research, there are difficult problems to be faced before practical solutions can result. The foremost problem is that the relational constraints are *passive* knowledge which serve to destroy but not create. *Active knowledge* is probably necessary to achieve a satisfactory segmentation on which to operate. Beyond this, there is the problem of encoding knowledge as relational constraints to be somewhat fuzzy. Roads often do terminate at streams or open water so these features might well appear to be connected in imagery. Incorrect decisions at beginning levels of propagation could produce meaningless interpretations.

Region objects	Lineal objects
Urban U	Stream S
Open water W	Road R
Background B	Railroad RR

Figure 6.5a) Possible interpretations for extracted image objects

c(X,Y)	X connects to Y where X is a lineal object and Y is either a lineal or region object
p(X,Y)	X penetrates Y where X is a lineal object and Y is either a lineal or region object
i(X,Y)	region object X is inside of region object Y
a(X,Y)	region object X is adjacent to region object Y

Figure 6.5b) Set of relations observable for certain pairs of uninterpreted image objects.

	S	R	RR	U	W	B
S	c	p	p	p	c	p
R	p	p,c	p,c	p,c	-	p
RR	p	p,c	p,c	p,c	-	p
U	-	-	-	-	a,i	a,i
W	-	-	-	a,i	-	a,i
B	-	-	-	a,i	a,i	-

Figure 6.5c) Real world constraints expressed in terms of relationships allowed between objects.

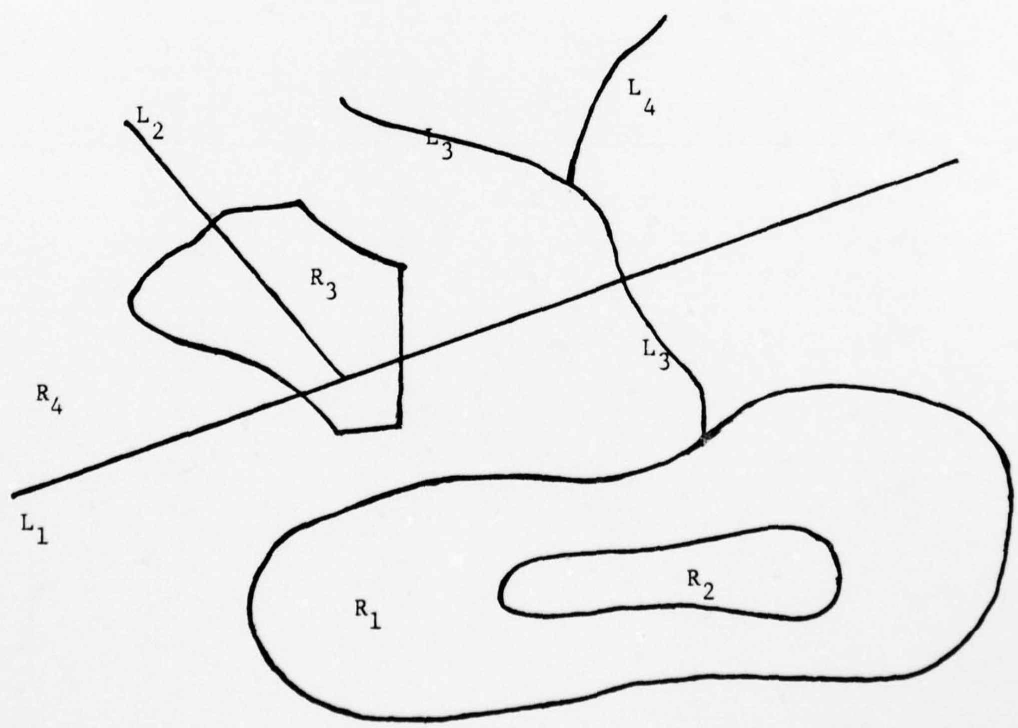

Figure 6.5d) Set of objects extracted from imagery

	L1	L2	L3	L4	R1	R2	R3	R4
L1	-	-	p	-	-	-	p	p
L2	c	-	-	-	-	-	p	p
L3	p	-	-	-	c	-	-	p
L4	-	-	c	-	-	-	-	p
R1	-	-	-	-	-	a	-	a
R2	-	-	-	-	a,i	-	-	-
R3	-	-	-	-	-	-	-	a,i
R4	-	-	-	-	a	-	a	-

Figure 6.5e) Relationships between objects of segmented imagery

Object	Possible initial interpretation	After filtering L1 against others	After filtering L3 against others	After filtering R1,R2,R3 against others	Final possibilities consistent with Fig. 6.5c) and e)
L1	R,RR,S	R.RR,S	R,RR	R,RR,S	R,RR
L2	R,RR,S	R,RR,S	R,RR,S	R,RR,S	R,RR
L3	R,RR,S	R,RR,S	S	S	S
L4	R,RR,S	R,RR,S	R,RR,S	R,RR,S	S
R1	W	W	W	W	W
R2	U,W,B	U,W,B	U,W,B	U,B	U,B
R3	U,W,B	U,B	U,B	U,B	U,B
R4	U,W,B	U,B	U,B	U,B	U,B

Figure 6.5f) Interactive removal of ambiguities in object interpretation by filtering (passing Figure 6.5e against 6.5c)

6.4.2 Map-directed analysis of B&W imagery

There are two severe problems encountered in the analysis of B&W imagery. The first problem - - needing global consistency in order to make local interpretations - - was discussed in the introduction to this section. The second problem is the difficulty of extracting meaningful curves and regions from the imagery to use as cartographic features. Noise and lack of contrast usually thwart bottom-up feature extraction procedures and fragmented and disconnected features typically result. Top-down analysis done under the direction of an existing base map could provide a solution to both problems.

Knowledge stored in a base map is not only highly specific to the geometry and content of the area being imaged but it is also easy to use in computer programs because the knowledge is locational in nature and easily registered to image positions. It would thus be easy to locate image pixels which are in the middle of a specific lake or road. Focused searches could be done for any lineals in the map archive which should be observed in the image. In this manner, interpretations could be established for a large number of feature fragments of the image. Then feature specific routines could be used to operate on uninterpreted data using the interpreted fragments as a guide. Roads and streams must be tracked to form connected networks, for instance. Parking lots could be scanned to count cars, known crop lands could be checked for plowing, etc. In this manner, all image features would be interpreted against cartographic features recorded in the data base.

The system described above would basically be a change detection system. Changes in the shape or location of critical features should alert reporting processes of the system. Critical regions of the imagery should be scanned for the appearance of features not mapped. These new features may be recent changes on the earth or may result from an image scale that is larger than the map scale. Much experimentation is necessary to test the concepts discussed. Future items for research are given in Section 9.

6.5 Feature specific map adjustment

Many adjustments to the map data may be necessary before printing the map. Some of these will depend on the technique for producing the map and should not alter stored data; other techniques will alter the stored data. For example, in the case of a road penetrating a vegetation window it may be necessary to subtract the road symbolization from the window so that two colors of the map will not overprint. It may not be necessary to keep the two parts of vegetation in computer store, however. In general any lineal feature (road, drain, etc.) must be checked for overlap with any areal feature (forest, lake, etc.). Similarly any two areal features and any two lineal features need to be checked for overlap. Two overlapping areal features, i.e. urban and lake, may imply the need for cleanup, or at the lower level may require the creation of a composite class slice (as the case where large water and vegetation overlap indicates swamp area). Cartographic standards require that contour lines show cut and fill at road intersections and show the gradient of drainage. Contour lines are themselves symbolic and are not apparent in imagery, nor are the adjustments mentioned above. The symbolization of the road/contour and drain/contour intersections can possibly be done when tracking in the elevation matrix. It should be noted in passing that contour features usually dominate in the storage and plotting considerations of automated map making and that adequate cartographic products could be produced more economically by bypassing contour adjustment. Finally we must consider the printing of place names, road numbers, point symbols, etc., on the map and the possible suppression of other information. On a typical topographic map most of these symbols will be printed on top of other features with little clutter. Road numbers, however, are not often superimposed on the road feature but are "cut out" of it. Once again it should be noted that faster, more economical map production is possible by ignoring the adjustments of name and point symbol placement.

6.6 Addition of information not apparent in imagery

Aerial imagery cannot supply all information to be mapped. Political boundaries, pipe lines, air routes, etc., may not be visible in imagery and may have to be entered by other means. Such data can be entered as polygonal or Freeman encoded information by a human operator tracing over the feature or giving successive points along it. Point data from any source can be entered into the system by an operator working in either the output map coordinates or in some standard coordinate system. Coordinates can be pre-assigned, for example by field survey techniques, or can be generated automatically by computer when an operator interacts with a display of the area.

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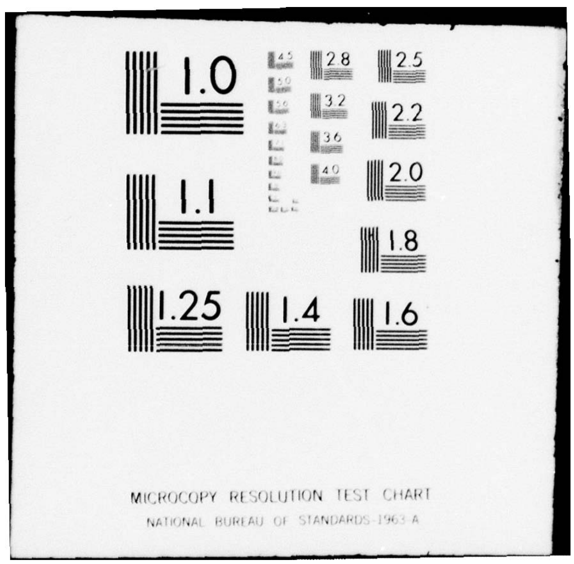
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Names of places and features must be added to a map as indicated above. Each feature identified in the map archive can be assigned a symbolic name, i.e. "Dismal swamp", "Buffalo crossroads", "Greenwood district", etc. Once assigned to features of a symbolic map, names can be transplanted to new imagery by correlating features of the new imagery with the archived features. Certain features can be tagged as <u>prominent features</u> in the archive and these can be used to establish a coordinate transformation between a new image and an archived map (Van Wie, 1977, and Barrow, 1977). Once a coordinate transformation has been established then all other less prominent points can be directly mapped from the archived map to the image. Identification of points in this manner leaves the problem of printing names on the map so that they do not overlap one another.

7. ACES process control

Available knowledge for cartographic feature extraction is discussed in Section 5 while the extraction of the features themselves is covered in Section 6. In this section details of the process controlling feature extraction and knowledge application are examined. The purpose here is to consider a particular example rather than to study several possible alternatives. A general assessment of some alternative mechanisms in knowledge engineering is given in [Barnett 1977]. Since the image interpretation tasks at hand are varied and complex, it is likely that no single mechanism offered by A.I. will suffice but rather a combination of several will be necessary.

Figure 7.1 presents knowledge-based image interpretation as a simplified sequence of 5 steps. At each of the 5 steps knowledge of some form is applied in refining the analysis. If two knowledge sources do not interact in any decision step, then it is possible to implement the knowledge sources in different manners. The results of analysis must be given in the same image description terms so that there is proper communication between processing steps. The general operations shown in Figure 7.1 should behave as specified in Table 5.1. The control of the individual processing steps themselves can be very complex depending upon the type of knowledge engineering done. Description of this complexity is avoided at this point in the research.

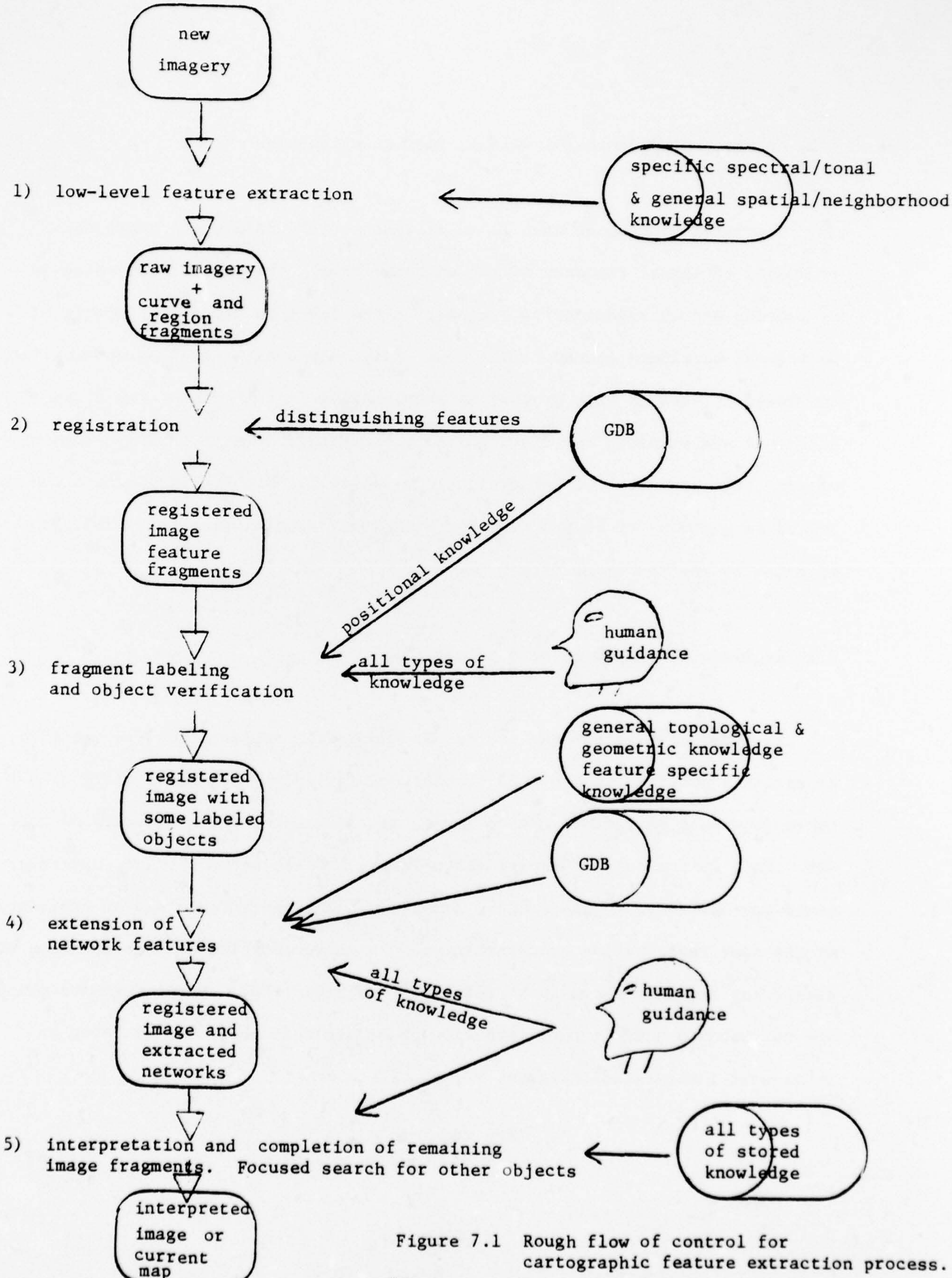

Figure 7.1 Rough flow of control for cartographic feature extraction process.

7.1 Preprocessing/general low-level feature extraction

The first processing step is to extract curved edges which represent fragments of lineal features or region boundaries. The goal of this step is to provide enough evidence for registering the image to the vast resource of positional knowledge stored in the GDB. Only very general spatial/connectivity knowledge is used in this processing step, making it very fast. The curve fragments are examined for distinguishing properties such as having a segment of very high curvature or 0 (straight) curvature. The curve fragments are described as a string of points together with their special properties and are adjoined to the raw image data.

7.2 Registration of image data to the GDB

In order to make maximum use of GDB knowledge, registration is attempted as early as possible in the ACES process. This is done by "correlating" the curve fragments extracted in step 1 with distinguishing curve segments of the GDB. This can be done by trying all pairwise matches between image curve segments and GDB curve segments until a maximum number of matches can be explained by the same registration transformation. An implementation of this matching via clustering has been shown to be feasible [Stockman 1978]. Curve segments which are not matched under the registration procedure must be processed later in subsequent interpretation steps.

7.3 Curve segment labeling and object verification

Any curve segment that matches a curve segment of the GDB is subject to immediate interpretation and labeling. Because of its known position through registration, the curve segment is known to be a portion of a stream feature, road feature, land-water boundary, etc. Other attributes of the feature become known through association; for instance, the name of a road, its width and material composition. Objects which were completely extracted during step 1 are now completely interpreted, while incomplete objects must be further processed in future steps.

7.4 Extension of network features

Networks such as roads and stream networks can be extracted under GDB guidance by starting with appropriate curve segments from the image and extending the curves through image points with fainter image features. An algorithm is needed which will test the conformity between mapped features and observed pixel properties and will implement topological, geometrical, and feature specific knowledge. Mapped features drawing no support from image data should alert a human interpreter for change analysis and possible revision of the GDB.

7.5 Final change detection

After step 4 most of the edge and curve activity of the new imagery will have been interpreted relative to the GDB. Further clean-up and search is required. First of all there will be curve segments which are present in the image but not the map. These may be due to noise or artifact or may indicate significant objects which are new or which were not mapped due to the scale or purpose of the GDB. Deletions of noise or artifact, or completion and interpretation of real objects will require all knowledge sources available in the preceding steps 1,3 and 4. In particular, an interactive human user may be called into the decision-making. There may be features which are mapped which have no corresponding curve data in the image. For these cases, a top-down verification procedure should be called to gather detailed evidence about the object's presence. Failure to detect the mapped object should either alert the human consultant or result in special symbolization on a preliminary cartographic product. Finally, certain focused searches should be performed in order to check for new objects which were not previously mapped and which yielded no edge activity in the preprocessed image. For example, drainage networks could be scanned for new bridges, road networks could be scanned for new connections or for vehicle activity.

8. Outstanding problems for ACES

Even a modest ACES system will be a complex system built on the most recent accomplishments in computer science, cartography, and electronics. Many installations are currently implementing, or have implemented, systems which are designed to register Landsat imagery to maps for interactive map update. Problems whose current solutions are regarded as good enough to support such systems are as follows.

- Radiometric correction
- Geometric correction
- Registration
- Regridding

Current systems still require the human for feature extraction and making map revision decisions. Problems remain for the automatic extraction of features and the management and use of real-world knowledge necessary in that process. Certain aspects of these problems are discussed below.

8.1 Extraction of primitive image features

In the opinion of the author, no research has demonstrated that satisfactory low-level primitive extraction can be accomplished automatically on a varied set of imagery. What is needed is a reliable procedure for segmenting imagery into primitive regions or boundaries. It appears unlikely that accurate and detailed segmentations can be gotten without the direction of knowledge at a very high level. Accepting this conclusion, one must then hope that enough accurate detail can be extracted automatically so that sufficient context is available to efficiently evoke the correct knowledge to interpret the remaining weak detail. This implies a combined data-directed and knowledge-directed procedure for primitive extraction. Control of such a procedure is a problem of much current interest in A.I.

8.2 Encoding and using knowledge

Several sections of this report have discussed the use and encoding of knowledge. Many obvious examples have been given where a priori knowledge was necessary and sufficient to interpret imagery. Certain of these applications of knowledge were even easy to program for automatic decision making. However, there is yet no knowledge encoding and manipulation paradigm that can implement a rich set of geographic information. Perhaps the most useful device currently available is to use a priori positional (iconic) knowledge stored in a geographic data base. This device has not received development in proportion to its potential, partly because of the difficult access to GDB's in the A.I. community and partly because of the research community's infatuation with higher level knowledge sources.

8.3 Detection and treatment of ambiguous situations

The research community has not yet learned to handle ambiguous situations with automatic programs. This is a fundamental issue. The problem may also be viewed as the problem of switching to higher levels of knowledge application to make decisions. Heterarchical approaches, which change levels whenever the context arises, have been tried with astonishing success in small domains [Winograd 1971], but the approach seems to be unmanageable in rich domains. Hierarchical relaxation is being tried [Hayes 1977]. The idea is to preserve all possible ambiguous interpretations at analysis level i and pass them onto higher levels i+j for refinement. The method will apparently suffer from an explosion of possibilities which level i is too uninformed to dismiss;but, results are not yet in.

Concrete examples should be considered before continuing. In region growing, the decision must be made to merge or not merge a given set of pixels with a neighboring set. The two sets of pixels have different properties but they are more similar in properties than any other pair of sets. By switching to a higher level where it might be known to which object(s) the two sets of pixels belong, the merging decision is easily made - - merge only if both sets are from the same object. Under a relaxation approach merging could not safely be done because it will be irrevocable at a higher level, and possibly be incorrect. A lineal feature connecting to and disappearing in a region feature might be a road disappearing in a forest canopy, a road terminating at an open water boundary, a stream dumping into open water, or a stream disappearing under a forest canopy. Resolution of the situation can be handled at a level higher than the lineal tracker, especially by relaxation labeling as done in Section 6.4.1, but the information might be critical for continued performance of the tracker. Should the tracking continue into the region to which the lineal has connected?

8.4 Control of ACES interaction with a human interpreter

Although ACES would ideally be totally automatic, this goal does not seem warranted for the near future and human guidance must be used when appropriate. But how should the interaction be controlled? The human is neither desireous nor capable of communicating with computer algorithms in terms of computer problem representations; i.e. data structures, state descriptions, prenex mormal forms, probabilities, etc. Humans are masters of the linguistic and visual domains. Fortunately the task is in the visual domain and good hardware devices are available for graphics. The linguistic domain, unfortunately, is not as well understood as many researchers would have us believe - - again because of the problem of a priori knowledge. Humans can efficiently supply global chunks of knowledge to the computer process, but not local chunks. Joining the man and machine is likely to require a solution to the context switching problem discussed in Section 8.3.

8.5 Change detection

In comparing raw image data to archived base maps a comparison is made between instructured real data and highly structured symbolic data. The equivalence class of raw images having the same symbolic map is very large due to nuances such as lighting differences, season change, or sensor change, or due to the objectives of interpretation. Do we map a puddle on the village green, or a ship passing through a canal? Ultimately, change detection must evaluate significance and hence must be implemented using high levels of knowledge.

8.6 Multidate functioning

Use has been made of multidate Landsat imagery for land classification, especially for vegetation classification [Kalensky 1974]. We should assume that registration procedures are currently good enough to produce useful multidate imagery although there will be confused areas near region boundaries. Road tracking may be done better in winter imagery while vegetation regions might better be gotten from summer imagery. Crop classification requires imagery from several dates. Management of multidate image data and use of it, together with temporal a priori knowledge, in mapping decisions presents another problem for ACES control and knowledge base.

9. Items for future work/research

The preceding sections of this report have roughed out paradigms for automation of image analysis in the production of cartographic products. The principle conclusion reached from the assessment of pattern recognition and artificial intelligence techniques is that useful automation will not be obtained unless large amounts of a priori real world knowledge is available to image analysis procedures. It is also evident that only a small fraction of knowledge available to a human interpreter may be available to an automatic process, largely because of limitations in encoding knowledge, in combining knowledge (in supporting or contradictory manners), or in accessing the knowledge or the data on which it is to operate. Knowledge engineering in A.I. has progressed only to the point of establishing expert systems in very limited domains. Examples of such systems are MYCIN [Shortliffe 1976], PROSPECTOR [Duda 1977], and HEARSAY [Reddy et al 1973].

Automatic image analysis necessary to fully support cartographic compilation would require far more sophisticated knowledge than what has previously been embodied in any existing expert system. However, it should be possible to perform several compilation tasks using current techniques. The most promising approach appears to be that of encoding in the knowledge base knowledge of only a positional nature and foregoing the storage of other types of knowledge. Other types of knowledge may reappear as procedural knowledge in specific processing tasks.

Encoding positional type knowledge allows straightforward comparison of new data with knowledge stored in the data base according to geographic position. This should allow simpler programs with acceptable computational complexity. It might be further argued that the "neighborhood of applicability" of positional knowledge be small so that array or raster processing is possible in applying the knowledge. In addition to simplicity there is a stronger reason for applying positional knowledge, and that is that we already have huge amounts of positional knowledge encoded in our current cartographic data bases. Human digitization of cartographic features could then be reviewed as a bootstrapping process for further automated analysis. Items of future work directed toward completion of the steps necessary for map-guided interpretation are discussed below.

9.1 Registration of images to base maps

To unlock positional knowledge stored in a map archive new source imagery must be registered to the symbolic representation in the archive. It is always known from navigational technology approximately what area of the earth is imaged and thus appropriate areas of archived symbology can be accessed. Local adjustments will be necessary to rotate, translate, stretch, or deform the image data so that points with global archive coordinates can be located in terms of image coordinates, or visa versa. These adjustments must be made by recognizing the correspondence between key (control) map and image features and defining the registration transformation from the known corresponding features. Unique point features are often chosen for control and block correlation is used to automatically detect the correspondence between map and image points. Unique edge features are also useful for registration. Arnold [1977] has asserted that point features are typically better for natural scenes while edge features are usually better for scenes with man-made structure. The greatest difficiency of current automatic registration procedures is that feature correspondences are decided upon one pair at a time. Correspondence errors are frequently made and contribute to inaccurate registration transformations. L.N.K. has recently developed a registration concept using clustering evidence based on possible pairwise correspondences [Stockman 1978]. The transformation that explains the largest set of feature pairs is chosen. A fair proportion of incorrect correspondences can be tolerated and will have no effect on the resulting transformation. Although the technique has proven successful in tests on 3 different data sets more development and testing is required. First of all it must be tested on natural terrain. Secondly, the technique must be adjusted to handle other than RS and T registration transformations.

9.2 Detection of lineal cartographic features in source imagery

If registration as described in Section 9.1 is to be accomplished certain key features must be acquired in the absence of the archived data. In particular, curved edge segments representing lineal features (roads, streams, etc.) or the boundaries of regions (land-water, forest-field, etc.) must be gotten in a totally automatic fashion. For scenes with much man-made structure it is easy to get a sufficient set of edge features, but there may be problems with natural terrain. More work needs to be done with natural terrain and point features to insure that registration can be successfully accomplished.

Techniques must be developed for tracking the paths of archived curves in the source imagery. The registration transformation allows points of the GDB to be positioned in the imagey but perfect feature correspondence may not be achieved pointwise because of 1) local distortion (i.e. no real change), 2) insignificant change in the feature (i.e. land-water boundary change due to the tide), and 3) significant change in the feature (i.e. the widening of a road). Many tracking techniques exist but more research is required in order to interpret the differences between archive and image tracks which will frequently occur.

New lineal features in the source imagery must also be extracted. One assumption that can be made from a priori knowledge is that new lineals must connect to an existing network. Techniques for tracking archived lineal features and detecting new connections should be developed.

9.3 Analysis of regions in source imagery

Region content of source imagery must be checked for significant change with respect to the GDB. Changes may consist of changes to the boundary or to the interior of the region. Changes to the boundary of regions may be detected by the same approach used for lineals in Section 9.2. Another approach based on tonal or textural pixel features and useful for checking the interior of a mapped region for change is as follows. Let R_m be a (discrete) set of points specifying the interior of region R in the GDB. Let R_i be the corresponding set of image points of R gotten via the registration transformation. Histograms of the features of the set of pixels R_i provide information on the structure of the region. A major peak should exist in each histogram indicating region pixels while minor peaks should exist for non-region pixels. Large minor peaks could be due to a change in the region boundary or to the introduction of new objects in the interior. The structure of the peaks should be most significant and should be independent of uniform change such as a sensor calibration shift, lighting condition, or even seasonal change. In certain cases absolute or relative peak displacement could be interpreted. In any case the region feature is mapped, and hence known, so that feature specific interpretation is possible. Consider a mapped lake with unmapped islands appearing in the source imagery. The tone of the island would differ from that of the water and two distinct peaks would be visible in the histogram. As a second example consider the browning of a deciduous forest or crop in the Fall. A definite histogram peak shift would be observed in the green band of MSS data. For resource monitoring this may be interpreted as significant change but for cartographic purposes the similar peak structure is indicative of no significant change. Map-guided region analysis as described here is another topic for future work.

10. Conclusions

The key problem in automatic cartographic feature extraction lies in the use of knowledge necessary for the extraction process. Knowledge must be applied in various forms and at various levels of interpretation. The use of knowledge in a rich domain is the central issue in A.I. today. Achievements have only been impressive where limited domains were considered [Winograd 1973, Duda 1977, Feigenbaum 1977]. It is therefore presumptuous to expect at this time a paradigm to explain the complete interpretation of source imagery, and no such unified paradigm was developed in this report.

It is possible to consider paradigms which address part of the interpretation process. That is, there are candidate partial theories which either operate at certain levels of the interpretation process, or which operate at multiple levels but implement only a fraction of the available knowledge. The paradigm of map-guided interpretation seems to be the most promising at the current time. This paradigm depends upon the registration of source imagery to the positional knowledge stored in a geographic data base (GDB). Useful GDB's currently exist and application of positional knowledge in a computer is straightforward. Source imagery from an area without a base map could not be handled under this partial paradigm and would have to be handled by current manual techniques. But, by such "bootstrapping" of knowledge, the system could be automatic on repeat coverage.

Since humans can readily apply general knowledge in analyzing scenes never before viewed, paradigms other than map-guided interpretation are of great interest. In particular, bottom-up feature recognition seems to be necessary. (It is also necessary for registration in the map-guided approach.) The ability of humans to interpret black and white photographs is particularly amazing in light of current difficulties with automatic interpretation. A. I. is currently hung up on the problem of scene segmentation and it is the conclusion of this study that very high level knowledge is necessary in order to segment black and white (B&W) imagery. This is because global spatial relationships and causal relationships not evident in the data itself are necessary in order to determine the function or content of objects in the scene.

The application of high levels of knowledge in the bottom-up interpretation of black and white imagery should be vigorously pursued. However, for near-future automation of cartographic feature extraction it is recommended that attention should be paid to MSS data. Use of MSS data permits the process of symbolization (interpretation) to occur at a very low level in the processing. This can reduce the volume of data and the amount of ambiguity passed on to higher level analyses. Current deterrents to MSS use, i.e. registration, resolution, cost and tradition, appear to be practical not theoretical considerations.

Under the top-down, map-guided, paradigm both B&W and MSS imagery can be handled, although feature tracking and verification would be more difficult (theoretically) in the B&W case. Sections 6 and 7 sketched an ACES system structure that would perform map-guided interpretation. For practical reasons a human consultant is also in the process. Further research and development is necessary to test and perfect the proposed concepts in map-guided interpretation. There are interesting problems for future work, and hopefully large gains to be made in automated map compilation.

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