

# CONTROL STRATEGIES FOR AN EXPERT SYSTEM TO INTERPRET LANDFORMS

*Abdullah Al-garni and Tony Schenk*

Department of Geodetic Science and Surveying, 1958 Neil Ave., Columbus, OH 43210-1247

*Douglas S. Way*

Department of Architecture 190 West 17th Ave., Columbus, OH 43210-1368  
The Ohio State University

**ABSTRACT:** One of the problems of interpreting landforms by an expert system is the definition of an initial space state by reducing the infinite number of landform types to plausible candidates. In this paper we focus on the initial space states. In particular, we investigate the set size of plausible candidates, and the associated control strategy and search techniques. The comparison of different strategies and techniques in view of landform identification and terrain analysis lends itself into recommended specifications of an expert system with which the problem should be solved.

## 1 BACKGROUND

Expert systems and their roles in image interpretation receive great interest nowadays (Argialas, D., 1988; Mintezzer, O., 1989; Bolstad, P. et al., 1991). Artificial Intelligence (AI) is defined as “*the study of how to make computers do things, which at the moment, people do better*” (Rich, E., et al., 1991). The problem of image interpretation is in quite compliance with this definition; and therefore, image interpretation is recognized as an AI problem.

Expert systems are considered as “*vigorous part of the burgeoning field of artificial intelligence*” (Edmunds, R., 1988). Many definitions of expert system exist today. Bowerman, R., et al., 1988 define it as follows: “*An expert system is a system of software or combined software and hardware capable of competently executing a specific task usually performed by a human expert.*” One of the most important aspects of an AI system is the search strategy (Patten, J., 1991; Rich, E., et al., 1991; Barr, A., et al., 1982). After the knowledge acquisition is completed, a suitable search method must be selected.

Today, two main types of limitations can be observed in the AI field. These limitations are technical limitations, such as storage problems and theoretical limitations, such as the general lack of understanding that characterizes the field of AI, vis-à-vis the way human minds process knowledge.

With the rapid advancement in the hardware technology, the technical limitations become less significant. The theoretical problem is improving slowly, and acceptable approximations to human reasoning are available. Scientific experiments are essential to provide suitable theoretical bases about how human minds process large knowledge bases in a matter of microseconds.

In the next section we analyze the problem of interpreting landforms based on terrain analysis. Then we investigate different search strategies followed by developing a control strategy that takes into account the technical and theoretical limitations of AI. Finally, we describe a rule-based program that combines the *establish-and-refine* and *ordered state* search strategies.

## 2 STATE SPACE SEARCH AND CONTROL STRATEGIES FOR ITA

To provide an acceptable state-space search and control strategy for *Image Interpretation Using Terrain Analysis* (ITA), a conceptual view of the problem should be investigated. There are three general factors based on which a control strategy can be qualified for an ITA problem. The first factor is the nature of the problem, which can be revealed based on a careful task analysis. The second factor is the experts' methods of attacking the problem in the real world. The final factor is the intended capacity of the system (scalability).

### 2.1 A Real World Human Model for ITA

Before any strategy can be devised for an expert system, a proper task analysis must be performed (Chandrasekaran, B., 1992 and Patten, J., 1991). The following paragraphs discuss ITA for the purpose of identifying landforms and deducing their parent materials and characteristics for site analysis and evaluation.

First, the ITA task is properly accomplished by experts in the field but not by computers at the moment. Therefore, landform identification for site evaluation purposes is commonly acknowledged to be an AI problem. The other aspect of the problem is that while many facts are well documented in different sources, such as books, reports, and maps, the most important knowledge for ITA is written nowhere but in the minds of the experts. This knowledge contains the strategy of approaching the problem at different circumstances.

To the question “How did you do it?” an expert may reply “It is easy! Well...I know it, but I do not know how I know it”. It is this part of the problem that points out the missing links in the chain of the theoretical aspects of AI (Patten, J., 1991). Also, this part of the puzzle calls for more research and exploration to uncover the high level of intelligence required for introducing AI systems into image interpretations in general.

ITA possesses two important AI properties. First, the

problem consists of many concepts that can be decomposed, within a general domain, into many subconcepts according to certain criteria (Hoffman, R., 1989a; Mintzer, O., et al., 1984; Mintzer, O., 1988; Strahler, N., 1981; Way, D., 1973; Zuidam, R., 1985). The other property of the problem is the way the solution is obtained by a human expert. At the beginning the solution is very general; then it is refined until specific conclusions are reached (Way, D., 1992). This property, called coarse-to-fine property, is more obvious in relatively hard and very hard (complex terrain) environments. The coarse-to-fine property is known in AI fields as *hierarchy classification* property. These two properties of the problem are indicative and to a large extent determinative of what control strategies should be devised in AI systems that are to be developed for the ITA problem.

Analysis of processing more than forty models in the field, processed by a recognized expert, indicated that a human expert analyzes the ITA problem in a consecutive logical way. Figure 1 shows a human analysis model for the problem. The model consists of five major phases or modules:

1. Adjustment module
2. Initial settings module
3. Transition phase module
4. Hypotheses module and
5. Verification module.

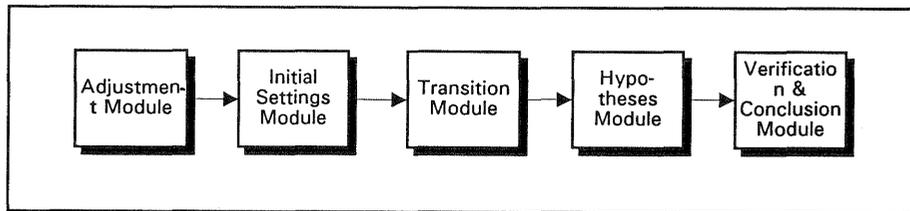


Figure 1: ITA Modularity as Processed by Human Experts in the Real World.

Many experts do not realize that they reason in this sequence. For instance, experts note the fourth and fifth phases but, often, not the first and third phases. This chain of logical analysis is very important to be realized by the Knowledge Engineer (KE) due to its essentiality in qualifying certain state-space search strategies over others for the ITA problem.

In the real world, an expert is sitting in his office and ready to provide interpretations and consultations for his customers. This is what an expert expects. However, he cannot predict what a customer's image will contain. That is, the expert might work on tens of stereo pairs, each containing different features, terrain, and characteristics. Analogously, an AI system for the ITA task should be ready for any type of tasks for ITA, but within the prespecified limits of the system. For instance, if the system was developed to identify thirty landforms on earth, it should be able to define any of these landforms at any time without an a priori expectation of which landform it will face with the next customer. This ability calls for an engineer to develop a systematic or methodological way of ITA that is general enough to cover the whole spectrum of the task.

This paper assumes a large system with definite number of goals. Figure 2 illustrates the properties of the task of ITA. The general configuration of the triangle indicates the coarse-to-fine property of the problem while the small squares inside the triangle portray the decomposability of the problem to smaller individual concepts. Depending on the granularity or resolution intended by the system, the reached and verified concept could be a single or several concepts. In fact, the ITA problem is methodological in nature (Avery, T. and G. Berlin, 1985) and modular in concept. The modularity of the problem is explained next as a set and subset concept.

## 2.2 ITA Decomposability Property

Using set theory, let the general concept of the above task be denoted by  $C_g$ , and let the first level of the decomposable concepts be a set  $L_1$  where

$$L_1 = \{C_{11}, C_{12}, \dots, C_{1n}\} \text{ such that :}$$

$$C_g \supset C_{11}, C_{12}, \dots, C_{1n}.$$

Then, it is necessary and sufficient for the ITA problem to be decomposable if it has:

1.  $C_g \neq \emptyset$ .
2.  $C_g \supset C_{11}, C_{12}, \dots, C_{1n}$
3.  $C_{ij} \cap C_{ik} = \{\emptyset\}$ , where  $j \neq k$

Now, let  $C_{11}, C_{12}, \dots, C_{1n}$

which are denoted previously by  $L_1$ , presents the coarsest level of the concept  $C_g$ , then

$$L_1 \in C_g.$$

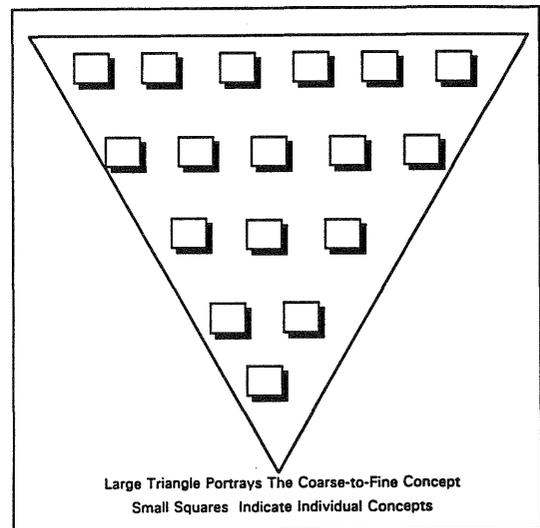


Figure 2: ITA With Coarse-to-Fine Concept and Decomposition Property.

By the same analogy,  $L_1$  may be further decomposed. Let

$$L_2 = \{C_{21}, C_{22}, \dots, C_{2k}\}$$

be the second level of the concept that is filtered from the first level. In a similar fashion:

$$C_g \supset C_{21}, C_{22}, \dots, C_{2k}.$$

Then the set relations

$$L_2 \in L_1; \text{ and}$$

$$C_{21} \cap C_{22} \dots \cap C_{2k} = \{\emptyset\}, \text{ where } L_2 \neq \emptyset$$

are held.

The same decomposition continues for the concept until  $L_g$  is reached, where  $L_g$  denotes the resolution level which contains the goal node:

$$L_3 = \{C_{31}, C_{32}, \dots, C_{3i}\}$$

⋮

$$L_r = \{C_{r1}, C_{r2}, \dots, C_{rm}\}$$

⋮

$$L_g = \{C_{g1}, C_{g2}, \dots, C_{gs}\}$$

where  $g > r > \dots > 1$ . Then

$$L_g \in L_{g-1} \in \dots \in L_1.$$

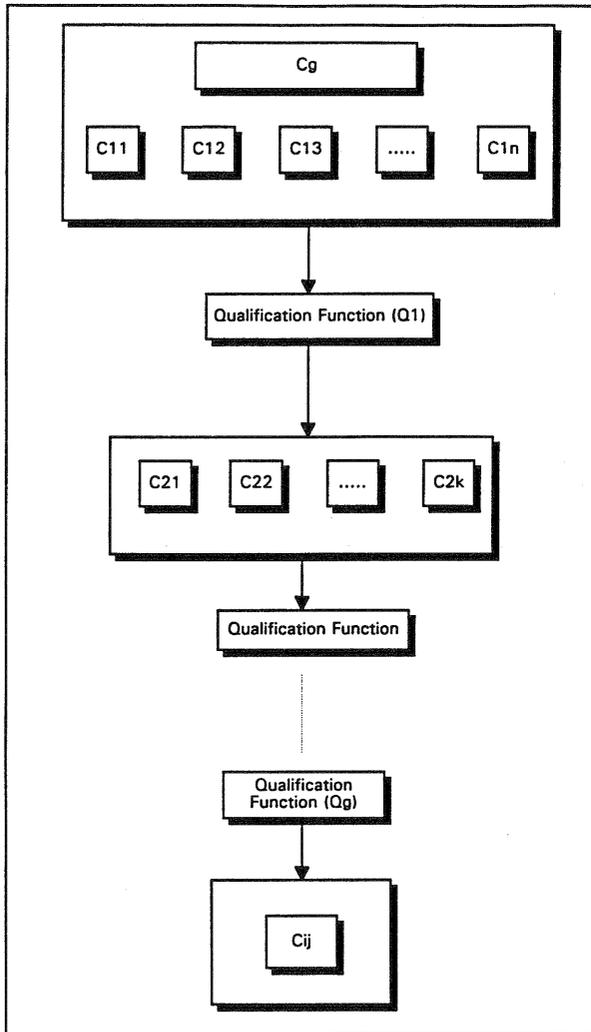


Figure 3: The Concept of Sets and Subsets of The ITA Problem.

Denote the level qualification factors that an expert uses to move from one level to the other by  $Q_1, Q_2, \dots, Q_g$ . These qualification factors are the criteria based on which

subconcepts are derived until the solution is reached. Figure 3 illustrates the filtration concept and the notion of sets and subsets of the ITA problem. (The reader is referred to Childress, R., 1974; Kaplansky, I., 1972; Eisenberg, M., 1971; Reed, G., 1977 for more information about set theory.)

The explained sets and subsets portray the solution path and should not be confused with the general problem configuration, which may appear quite opposite in a diagram. To illustrate the difference, Figure 4 combines the whole concept. More attention should be paid to the setting of the large triangle as opposed to the settings of the interior, smaller, triangles. Conceptually, these two triangles are similar in that both have coarser knowledge up and finer knowledge down. The difference, however, is in the final outcome of each. The larger triangle presents the whole spectrum of the problem. That is, all landforms existing on earth that the system may identify are listed at the bottom of the large triangle. In contrast, the smaller triangle presents only those landforms that are of interest and appear on a particular image. Therefore, smaller triangles represent a solution while the larger one represents the whole problem (domain). The individual events represented by the small triangles are eventually summed up to constitute the whole population.

### 2.3 Search Flow of The Human Model

Based on the previously mentioned properties and theories of the nature of ITA problem, it is fair to say that in the real world the absolute initial states of the problem are unknown at the first few moments. This general statement immediately implies unknown goals at the initial state space. For instance, an analyst is told to define all existing landforms in a stereoscopic pair of images. Before looking at the pair, the analyst has no way of knowing where to start and what to expect. This momentary vagueness is soon adjusted according to the adjustment module based on certain criteria in the very few starting steps of the interpretation processes.

This part of the problem (an unknown hypotheses) calls for an immediate forward tracking of the solution by the expert system (initial setting module). Likewise, the human expert is unconsciously conducting a forward search or tracking at his initial settings and scanning of the problem. As soon as the human expert handles the images, looks at them, and reads them, he narrows the problem and defines his starting points or what is called initial state-space. As mentioned previously, control strategy should be in a close compliance with human search strategies. Accordingly, at this level of discussion, the first conclusion is that the initial search control strategy should be developed to work in a forward-tracking (knowledge-driven) manner.

The next step of search control strategy conducted by human experts is to do further careful analysis based on well established criteria to prune all irrelevant concepts from the whole space, sticking only the candidate concepts. This middle level of the search can be either forward- or backward-tracking. The tracking method depends on how the expert attacks the problem to decompose it into subconcepts. If he has already developed a certain broad hy-

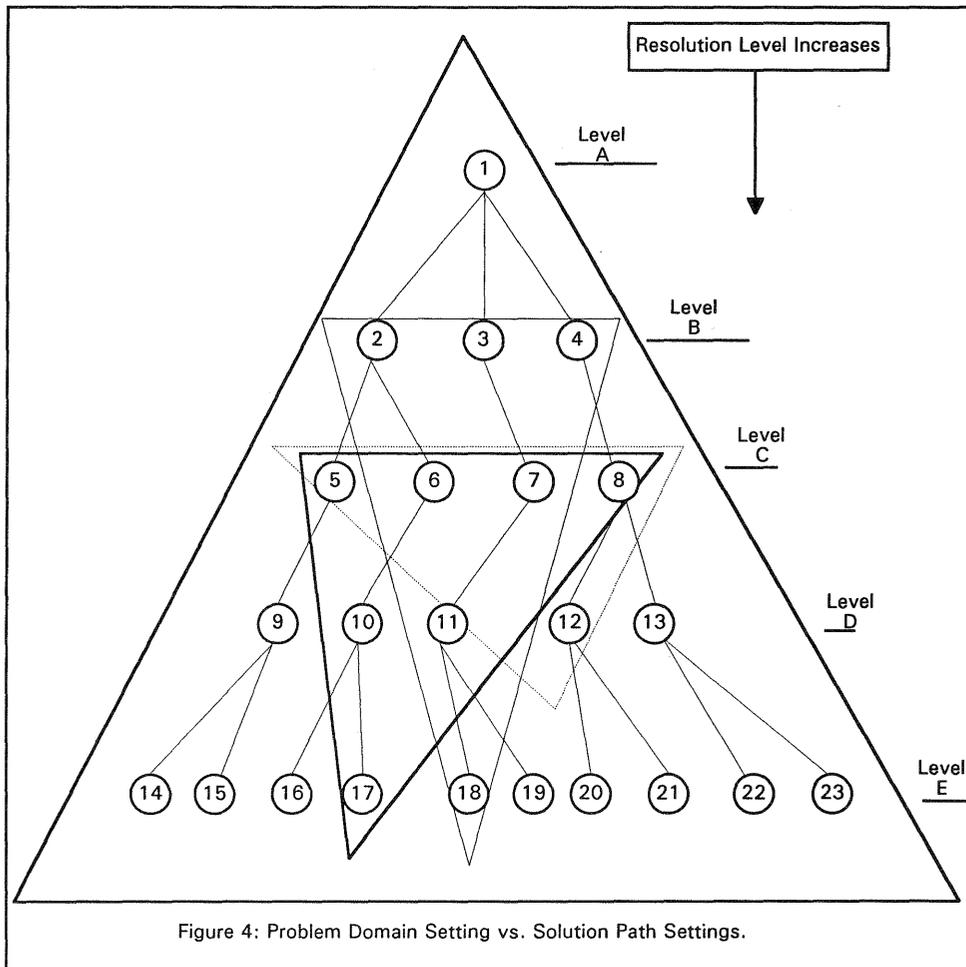
pothesis about several subconcepts, then he is doing a temporary backward tracking of this hypothesis in his mind. But if the problem is still too vague, a forward tracking may continue because the expert has not yet developed any goal to verify (transition phase module).

The third and last step achieved by the expert is to rank the possible and most promising concepts (landforms) in the image and to start to verify them one (or several) at a time (hypotheses module). This implies that, at this level of image interpretation process, a very determined hypothesis (goal or concept) is clearly defined in the expert's mind. Until the goal is verified or disapproved, the whole process is a goal-oriented (or a goal-driven) process. The AI system must follow the human way of attacking the problem and act accordingly. From here on, the rest of the process of the control strategy should use backward tracking for the knowledge search since some goals are developed (verification module). Since there is no absolute forward tracking in AI, it is important to realize that there is a dummy or transitional parameter so that the data-driven search can progress (Chandrasekaran, B., 1992).

viewpoint of image interpretation using terrain analysis. This paper concerns the third component.

The basic characteristics that any good control strategy should possess are the ability to maintain a dynamic character (motion) of the state-space and the ability to provide a systematic behavior to the whole space (Rich, E. and K. Knight, 1991; Chandrasekaran, B., 1990). The mobility property of any strategy provides the avenues to eventually reach the solutions to the problem under consideration. On the other hand, the systematic property of any strategy prevents the undesirable repeated exploration of useless state-space several times before the solution is reached (Patten, J., 1991).

The content and the organization of the system's knowledge base are influenced by the selected control strategy. The control strategy of a system becomes very obvious in tasks that use operators to modify the problem concepts in a multiple task-domain situation. The ITA problem needs several operator sequences at every level so that the next move is conducted intelligently. This property of the prob-



## 2.4 Qualifications and Implementations of Strategies

Like any other AI problem-solving system, the ITA expert system consists of three main components: a database, a set of operators, and a control strategy. Current research is carefully investigating all three components from the

lem exposes two different types of search theories. The first theory is called blind search theory or control strategy (e.g., breadth-first and depth-first search)(Barr, A., et al. 1982; Rich, E. and K. Knight, 1991). The second theory is called heuristic search theory or strategy (e.g. ordered state-space or best-first search) . These theories are illustrated by presenting three examples so that proper conclusions about the suitability of these theories to the

ITA problem are reached.

## 2.5 Blind State-Space Search Strategies

### 2.5.1 Breadth-First and Depth-First Search Strategies

Breadth-first search strategy expands the concepts (nodes) according to their proximity to the starting node or concept. Arcs can be used as a measure for node proximity. Accordingly, all possible operator sequence of length  $n$  is considered before any sequence of length  $(n + 1)$ . In the ITA problem this strategy declines in value as the system's scalability increases. If careful planning is not practiced before developing the expert system, this problem is dangerous for it may not be very obvious at the initial stages of developing the system.

As it should be understood, expert systems are developed incrementally (Jackson, P., 1986). That is, system development passes through three phases. The first phase is the prototype development of the system. Most often this phase can use the breadth-first search strategy, which can be of great advantage. The next phase is a transition phase. In this phase, the attributes, parameters, and number of landforms to be treated increase. At this phase the system's slowness becomes evident. The third phase of the development is the hybrid system phase. In this phase the problem spectrum is almost completely covered by the system.

Since the number of landforms on earth and their parameters and attributes are so large, a very big knowledge base can be foreseen. This fact makes the breadth-first search strategy unacceptable since its blind behavior causes time and space limitations. The limitations can be visualized by looking at the exponentially expanding nodes in Figure 4. In breadth-first search, if node 23 is an assumed hypothesis in the tree, then this hypothesis cannot be reached until the system searches the whole tree, starting at node 1 on level A through the last hypothesis just before hypothesis 23 on level E (For basic algorithms for this strategy the reader is referred to the references at the end of this paper).

The depth-first search strategy operates as another blind state-space strategy. This search strategy gives the starting node 0 depth, and from there all other nodes are numbered so that the depth of any node is 1 more than the depth of its predecessor. Depth-first strategy expands the most recently generated node by following a single path through the state space downward from the starting node until a goal is reached or a dead end is found. Figure 4 illustrates how depth-first search works. Notice here that the nodes 1, 2, 5, 9, and 14 are treated in the first processed single path, but in the next alternate path operations start at node 9. The process continues until hypothesis at node 23 (an assumed goal) is reached. Thus, after the initial settings of node 2 and its branches are explored, the search starts back at node 3 and explores initial settings of its branches.

Conceptually, these methods of state-space search are incompatible with human expert methods conducted for an ITA task in the real world. It should be realized, how-

ever, that this conclusion is based on pure blind search methods in which no criteria are developed to qualify the promising nodes to be explored amongst the list in every level in the state-space problem. When a set of qualifying criteria is developed for these methods, a new and more sophisticated state-space search and control strategies are obtained, which are closer to the human way of reasoning about the

### 2.5.2 Heuristic State-Space Search for ITA

Heuristic control strategy assesses various operator sequences and signalizes or instantiates the most promising sequence (Barr, A. and E. Feigenbaum, 1982). In fact, heuristic search strategies use certain criteria to direct the search in the state-space of the problem. Based on these criteria and based on the nature of the ITA problem, heuristic state-space search and a combination of forward and backward chain reasoning constitute a set of control strategies that meet the conceptual aspects of the ITA problem; and, therefore, this set is implemented by this study for this problem. This type of search is justified by many facts, some of which were described previously and some of which are discussed next.

Representing the knowledge in the expert system according to the logic of the human expert is a prerequisite in developing control and search strategies for the system. This prerequisite stems from two essential factors. First, the expert has to understand the KE's real attempts to model the expert's own expertise and, as a result, the expert gains the confidence to test and evaluate the system's success based on his knowledge and familiarity with the main workings of the system. In relation to this issue, the end user's acceptance of and confidence in the system are more likely to be attained if the knowledge representation and control strategy schemes approximate the expert's knowledge.

Second, the expert's strategy of representing and controlling the knowledge is a whole package of expertise that any AI system should maintain. In a heuristic search the ingredients of the ITA problem are the initial state, the operators, and the goal states (I.O.G). The main objective of the KE is to model the control strategy and logic that the human expert uses when connecting the initial state-space with the goal state-space through appropriate operators.

As can be concluded by now, the blind search of a state-space expands a very large number of nodes before a solution is reached. The reason for that is the arbitrary behavior of expanding the nodes without controlling the search mobility according to the properties of the problem at hand. As a part of the control strategy the triple (I.O.G) is assumed to be established. The rest of the control strategy is, then, to develop heuristic information about the ITA problem and to implement a search method which uses this information to effectively search the given space.

### 3 ORDERED ESTABLISH AND REFINEMENT SEARCH ALGORITHM (OERSA)

We develop a heuristic state-space search algorithm that will fit the ITA problem. This hybrid search strategy combines the properties of the well known *establish and refine* and *ordered state-space* heuristic search strategies. It is necessary to have a general understanding about what type of heuristic information can be used in searching the space of the ITA problem. This information includes heuristic strategy constraints and can be categorized according to its function into two different categories. The first category is a set of information that qualifies the most promising node to be expanded and which evaluates node successors to generate the best node amongst them. This type of information is used by the heuristic search strategies to eliminate the blind expansions that characterize breadth-first and depth-first strategies. The second category is a set of information that eliminates irrelevant nodes from the whole space.

The implemented algorithm represents the general idea of the heuristic search methods as compared to the blind search methods. The general concept of the OERSA is that it works globally on the total set of nodes that are not yet expanded, and it evaluates them to expand the most promising successors or nodes only. The evaluation function  $Q$  is a problem dependent. In the ITA problem, the qualification function  $Q$  should be the similarity measure between the current space state node and the goal node instead of the distance or difficulty qualification measure that is used by some other problems. In some instances the  $Q$  function in the ITA problem is developed based on elimination criteria, where refinement is conducted for the established nodes. Figure 5 represents small portion of the rules and screens of the expert system which contains OERSA.

The OERSA, implemented by this study, is as follows:

- Start the adjustment module by applying global qualification function  $Q$  to the ITA space in order to establish the initial state node  $S$ .
- Prepare a list in the initial state node  $S$  and evaluate the individual elements in the list according to the  $Q$  function (an evaluation function).
- If the node  $S$  is empty, then report a failure as an indication that no solution exists.
- If  $S$  is not empty, then according to the  $Q$  function establish the most promising concept (concept  $i$ ) in the node.
- Call a recognition agent and test concept  $i$ , if the concept is a goal node, then report the proper conclusions and exit with success.
- If concept  $i$  is not a goal node, then establish successors of concept  $i$  and refine each successor node, say concept  $k$ , using the  $Q$  function:
  1. If concept  $k$  is new, then list it among the other unexpanded concepts and give it a pointer to its parent node to trace its path toward the goal concept if found later.
  2. If concept  $k$  is not new, then call the probability function, compare  $k$ 's current value with the previously calculated one, and make proper substitutions. Refinement based on certainty factors are in effect at this stage of the inference process.
    - Return to step number 2 and continue.

### 4 DISCUSSION

The human strategy for interpreting landforms is systematic and of clear conceptual blocks. That is, the process is coarse-to-fine, in general, and is knowledge-driven until the initial space states are set; then the rest of the process is a goal-driven verification of the hypothesis. An AI system for the same purpose must closely follow the same general guide lines. It is not impossible, however, to follow other strategies that could solve the problem but will be characterized by two properties:

- The AI system will not act according to the human methods. This will lead to two conceptual consequences:
  1. The problem may be regarded as not an AI problem, which contradicts the reality of the ITA problem;
  2. The system will lack the property adhering in the word "EXPERT"; or
- The efficiency of the system, both time-wise and storage-wise, may be questionable, especially for large tasks.

It has been explained how each type of control strategy behaves as viewed from an image-interpretation perspective. In reality, both breadth-first and depth-first search methods are characterized by the mobility property that a good strategy maintains. The drawbacks of both, however, are listed here from an AI viewpoint and from the ITA viewpoint as well:

1. Incompatible with the human logic of solving the ITA problem.
2. Depth-first method may be trapped in the state-space and goes through an endless loop.
3. The breadth-first search is characterized by time and space inefficiencies.
4. In both methods, the obtained solutions may be not the optimal solution.

These drawbacks are not necessarily disadvantages for some other types of AI problems. For instance, in some other situations the following are advantages of these methods:

1. Depth-first search is fast.
2. Breadth-first search guarantees a solution if one exists.



Hoffman, R., 1989a. What is a hill? Computing the Meanings of Topographic Terms. In A. Kunz & U. Schmitz (Eds.) *Linguistic Approaches to Artificial Intelligence*. Duisburg, West Germany: University of Duisburg Press.

Jackson, P., 1986. *Introduction to Expert Systems*. Addison-Wesley Publishing Company.

Kaplansky, I., 1972. *Set Theory and Metric Spaces*. Allyn and Bacon, Inc. Boston.

Bolstad, P. and T. Lillesand, 1991. Automated GIS Integration in Landcover Classification. *ACSM-ASPRS Annual Convention; Technical Papers, Remote Sensing, Vol. 3.*, pp. 23-32.

Luger, G. F. and W. A. Stubblefield, 1989. *Artificial Intelligence and the Design of Expert Systems*. The Benjamin/Cummings Publishing Company, Inc.

Mintzer, O., and J. A. Messmore, 1984. *Terrain Analysis Procedural Guide For Surface Configuration*. Report ETL-0352. Engineering Topographic Laboratories, Fort. Belvoir, VA.

Mintzer, O. W., 1989. Research In Terrain Knowledge Representation For Image interpretation And Terrain Analysis, U.S. Army Symposium On Artificial Intelligence Research For Exploitation Of Battlefield Environment, 1-16 Nov, 1989 El Paso, Texas, pp. 277-293.

Mintzer, O., and J. A. Messmore, 1984. *Terrain Analysis Procedural Guide For Surface Configuration*. Report ETL-0352. Engineering Topographic Laboratories, Fort. Belvoir, VA.

Patten, J., 1991. CIS 630 "Survey of Artificial Intelligence I: Basic Techniques and CIS 730 Survey of Artificial Intelligence II: Advanced Topics". The Ohio State University.  
Strahler, N. A., 1981. *Introduction to Physical Geography*. John Wiley & Sons, Inc., N.Y.

Schenk, T., and O. Zilberstein, 1990. Experiments with a Rule-Based System for Interpreting Linear Map Features. *Photogrammetric Engineering & Remote Sensing, Vol. 56, No. 6*, pp. 911-917.

Quinlan, J. R. (editor), 1989. *Applications of Expert Systems; Volume 2; Based on the Proceedings of the Third And Fourth Australian Conferences*. Addison-Wesley Publishing Company

Reed, G. 1977. *Set-Theoretic Topology*. Academic Press, Inc.

Rich, E. and K. Knight, 1991. *Artificial Intelligence*. Second Edition. McGraw-Hill, Inc.

Way, D., 1992. *Landform Interpretation Sessions For Expert System Implementation at The Ohio State University*.

Way, D. S., 1973. *Terrain Analysis, Second Edition*. ISBN

Wyckoff, J., 1966. *Rock, Time, And Landforms*. Harper & Row, Publishers, New York.

Zuidam, R. A., 1985. *Aerial Photo-Interpretation In Terrain Analysis and Geomorphologic Mapping*. Smits Publishers, The Hague.