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Towards structured-knowledge models for landform representation

by

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with 7 figures and 10 tables

Summary. Three research efforts, each having produced an original, practical prototype computer system for terrain analysis are reported. First is the computational description and identification of eight drainage patterns through structural pattern-recognition. Drainage pattern-recognition was achieved by identification of network objects, attributes, and relations, as well a decision-tree classification strategy. The second effort uses a variety of expert-system methods and tools to address terrain knowledge-representation through the landform-pattern element approach and to construct prototype expert-systems for inferring the landform of a site from user supplied observations of pattern elements. The third effort develops a visual vocabulary of pattern-elements through a Macintosh-based hypermedia system consisting of interlinked pieces of definitions, graphics, and aerial images which can be browsed in a non-linear, non-sequential, user-defined manner. Finally the unifying aspects of the three approaches are presented. I conclude that landform-related knowledge can be organized through these structured models to assist understanding of what characterizes the landform interpretation process and to make it more explicit and rigorous.

Zusammenfassung. Der Aufsatz berichtet von drei Forschungsbestrebungen, von denen jede einen originalen, einsetzbaren Prototyp eines Computersystems hervorgebracht hat. Die erste Bestrebung umfaßt die computergestützte Beschreibung und Identifikation von acht Gerinnemustern durch strukturelle Mustererkennung. Die Erkennung der Gerinnemuster wurde durch die Identifikation von Netzwerkobjekten, Attributen und Objektbeziehungen als auch durch die Klassifikationsstrategie aufgrund eines Entscheidungsbaumes erreicht. Die zweite Bestrebung verwendet eine Auswahl von Methoden und Werkzeugen, die bei Expertensystemen Verwendung finden, um eine wissensbasierte Reliefrepräsentation durch Versuche zum „Reliefformmuster-Element" zu erreichen und zum anderen um den Prototyp eines Expertensystems zu konstruieren. Dieser Prototyp dient der Ableitung der lokalen Reliefform auf Basis der durch den Nutzer gelieferten Beobachtungen von Musterelementen. Die dritte Bestrebung besteht in der Entwicklung eines visuellen Wörterbuches zu Musterelementen durch ein Macintosh-basiertes Hypermediasystem. Dieses System besteht aus kombinierbaren Komponenten von Definitionen, Graphiken und digitalen Luftbildern, die in nichtlinearer, nichtsequenzieller und nutzerdefinierter Art und Weise durchblättert werden können. Schließlich werden die verbindenden Gesichtspunkte der drei vorgestellten Bestrebungen dargestellt. Ich ziehe die Schlußfolgerung, daß das auf die Reliefform bezogene Wissen durch diese drei strukturierten Modelle systematisch gegliedert werden kann, um das Verständnis darüber zu unterstützen, was den Interpretationsprozeß von Reliefformen charakterisiert und um diesen Prozeß offener und genauer zu gestalten.

Résumé. Trois efforts de recherche, dont chacun a produit un système original, pratique, prototype, pratiqué à l'ordinateur, sont ici rapportés. Le premier effort est la description et l'identification calculatrices de huit formes de drainage à travers une reconnaissance des formes structurées. La reconnaissance de la forme de drainage est réussite par l'identification des objects, des attributs et des relations du réseau, de même par une stratégie de classification en forme d'un arbre de decision. Le deuxième effort utilise une variété de methodes et d'instruments des systèmes experts, pour s'adresser à la représentation de la connaissance du terrain à l'aide de l'approche de l'élément de forme, et pour construire prototypes systèmes experts, qui aident à induire l'unité terrestre d'une région basé sur les observations des éléments de forme ramassées par l'utilisateur. Le troisième effort developpe un vocabulaire visuel des éléments de forme basé sur un Macintosh hypermedia système qui consiste des pièces entreliées de définitions, de dessins et d'images aériennes qui ne peuvent être feuilleter ni-linéairement, ni par ordre, mais définie par l'utilisateur. Finalement sont présentés les aspects communs des trois approches. Dans cet

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article on conclut que la connaissance attachée a l'unité terrestre peut s'organiser en utilisant ceux modèles structureux qui aident à comprendre ce qui caracterise le procès d'interprétation de l'unité terrestre et qui le fasse plus claire et rigoureux.

1 *Introduction*

Terrain analysis is the systematic study of image elements relating to the nature, origin, morphologic history and composition of landforms (WAY 1978, LILLESAND & KIEFER 1979, MINTZER 1983, MINTZER & MESSMORE 1984, DEROIN et al. 1990). Landforms are natural terrain units, usually of the third relief order, which when developed under similar conditions of climate, weathering, and erosion exhibit a distinct and predictable range of visual and physical characteristics. The landform is fundamental in representing and organizing topographic and geomorphic (and morphometric) information through the pattern-element approach to terrain analysis. The landform-pattern element approach is based on the following premise: any two terrain surfaces derived from the same soil and bedrock, or created by a similar process, occupying the same relative position, and existing under the same climatic conditions exhibit similar physical and visual features on aerial images, called pattern elements (WAY 1978, LILLESAND & KIEFER 1979, MINTZER 1983, MINTZER & MESSMORE 1984). The elements include topographic form, drainage pattern, gully characteristics, soil tone variation and texture, land use, vegetation, and special features (Table 1). The meanings of some of these generic topographic-terms have been analyzed by HOFFMAN (1985) and HOFFMAN & PIKE (in press).

Terrain analysis use the pattern elements, as well as maps and bibliographic information, to identify landforms, their parent material, and their engineering characteristics. The landform is inferred from pattern-elements of the site and then the parent material is inferred by its association with the landform. The discipline was developed by specialists who used image analysis as a source of terrain information for operations planning and construction projects (WAY 1978, LILLESAND & KIEFER 1979, MINTZER & MESSMORE 1984). It has wide applications in soil science, environmental inventory and mapping, in agricultural engineering, in structural geology, and in hazard and risk modeling (MITCHELL 1973, TOWNSHEND 1981, MINTZER 1983, DIKAU 1993).

Problem solving in terrain analysis commences with hypotheses about the landforms likely to occur in an area, by drawing upon the analyst's experience and auxiliary information specific to the region (MINTZER & MESSMORE 1984). Then he searches the aerial image, to find a match between the expected pattern elements of one of the hypothesized landforms – those found in texts and guides – and the observed characteristics. The analyst continues this procedure, until all the pattern elements are examined. If there is a significant match between expected and observed pattern elements, the identity of the landform is established. Otherwise, the next landform in the hypothesis list is investigated for a match.

2 *Rationale and Objectives*

Terrain analysis can be time consuming, labor intensive and costly. Its skills are a product of lengthy and expensive training. Therefore, it could help to at least partially automate this process. Computer-assisted interactive systems could aid training by introducing students to the decisions made by experts and by improving the reliability of interpretation. They could also provide a research vehicle to explore and test the landform-related knowledge.

Landform interpretation is still an art without a formal theory (RYERSON 1989, HOFFMAN 1987). The knowledge available in books is descriptive and fuzzy. A procedural framework for problem solving is missing: books do not elaborate on the strategies needed to guide a novice to the process required for landform identification. On the other hand, skilled experts routinely perform

Table 1. Some land-form-pattern elements and their types.

Topographic form	Drainage pattern	Vegetation-land use	Special feature
A-shaped hill	Anastomotic	Barren	Blowouts
Bold domelike hill	Angular	Cultivated	Cigar-shaped
Broad and level plain	Annular	Forested	Columnar jointing
Conical hill	Asymmetrical	Grass	Contour farming
Crescent-shaped hill	Barbed	Natural cover	Fan-shaped
Dissected plain	Braided	Rangeland	Fluvial marks
Drumlin shaped	Centripetal	Urban	Hummocky slopes
Fan-Shaped plain	Collinear	Wetland	Meanders
Flat	Contorted		Natural levees
Flat table rocks	Dendritic		Parallel ridges
Gently rolling	Deranged		Rounded boulders
Hill	Dichotomic		
Hummock	Elongated bay		
Isolated hill	Illusory		
Karst	Incipient		
Level plain	Internal		
Massive hill	Kettle hole		
Parallel laminations	None	**Gully shape**	
Parallel ridges	Parallel	U-shaped	
Pitted plain	Pinnate	V-shaped	
Plain	Radial	White fringed	
Ridge	Rectangular		
Ridge and Plain	Reticular		
Rounded Hill	Subdendritic	**Soil tone variation**	
Saw-toothed ridge	Subparallel	Black	
Sinkhole	Swallow hole	Dull gray	
Snakelike ridge	Thermokarst	Light gray	
Soft Hills	Trellis	White	
Soft rounded hill	Yazoo		
Star-shaped hill		**Soil tone texture**	
Steep Hillsides		Banded	
Undulating plain		Mottled	
Vertical slopes		Scrabbled	
Kettle-knob		Uniform	

landform interpretation. Implicit terrain-related knowledge enables the expert to directly perceive or indirectly infer landforms from aerial images. Expertise is not documented in textbooks and manuals and hence it is not explicit and unambiguous. It can not be easily taught, expanded, stored, transferred, replicated, and criticized. There is, therefore, a need to study the terrain-analysis reasoning process and, to better understand it develop a systematic framework for the recognition of landforms from aerial images (HOFFMAN 1985, ARGIALAS & NARASIMHAN 1988a and 1988b).

Towards that end, this paper reports on three efforts, each having produced a prototype computer system for landform interpretation (Table 2). The first is the computational identification of drainage patterns, represented in vector format, through structural pattern-recognition. This was achieved by identification of network objects, attributes, and relations, as well a decision-tree classification strategy. The second uses expert-system methods to address terrain knowledge-representation through the landform-pattern element approach and to construct prototype expert-systems for inferring landforms from user observations of pattern elements. The third effort

Table 2. Three structural methods of knowledge representation.

Method	Knowledge representation	Developed Prototype system
Structural pattern recognition	1. Objects and their attributes and values represent the unit elements of patterns	DPA
	2. Relations and associations represent the embedded organization structure subsisting between the objects	
Knowledge based expert systems	1. Facts represent the knowledge units expressed declaratively	TAX-1
	2. Production rules represent the structure embedded in the facts and strategies of reasoning	TAX-1 TAX-3
Hypermedia	1. Chunks of text, images, or video represent individual knowledge unit	VVT
	2. Links represent the structure of our knowledge that is the associations and relations between the units	

develops a visual vocabulary of pattern-elements through a Macintosh-based hypermedia system consisting of interlinked definitions, graphics, and aerial images which can be browsed in a user-defined manner.

3 *Computational methods and tools*

Three computational methods: structural pattern-recognition, expert systems, and hypermedia have been used to build the prototype systems. Advances in these areas have developed computer programs that can capture the knowledge structure underlying expertise in many fields and tasks (ARGIALAS & HARLOW 1990).

3.1 *Structural pattern recognition*

This method refers to digital image-analysis techniques that represent and recognize patterns in terms of their structure (GONZALEZ & THOMASON 1978, FU 1982). Often this structure is represented by rules expressing the juxtaposition of identifiable pattern elements, their attributes, and their interrelationships. Implementation of the structural approach requires the design of hierarchical and relational models, extraction of pattern attributes, and design of a classification strategy. In a hierarchical model, each of the top-level objects must be defined in terms of its lower-level objects; at the lowest level of description, the objects are primitives where each part above the level of a primitive has its own hierarchical description. Implementation of a hierarchical model requires objects to be organized systematically at all levels by attaching an attribute list to each node of the object hierarchy. One way to do this is to use relational tables. A pattern can be assigned to one of many possible classes based on computed pattern features and attributes. In the structural approach, a series of tests can be designed to evaluate the presence or absence of certain subpatterns, or pattern attributes and their values. These tests can then be embedded in a decision tree for pattern classification.

3.2 *Knowledge-based expert systems (KBES)*

Expert systems are a field of artificial intelligence that addresses complex, domain specific, problem solving that requires unique expertise (HAYES-ROTH et al. 1983, HARMON & KING 1985, JACKSON 1986). Their performance depends on facts and heuristics used by experts. Their success is determined by the effective computer representation of domain knowledge. Production rule-based systems are the most widely used scheme for knowledge representation. Factual knowledge is represented as object-attribute-value triples. Strategic knowledge is represented as sets of rules, of the form IF ["condition statements"] THEN ["action statements"], that will be checked against a collection of problem facts to infer new facts. When a problem satisfies or matches the IF part of a rule, the action specified by the THEN part is performed. The execution of a set of rules, commonly called rule-chaining, results in a new set of facts which is added to the existing list, which trigger other rules. In such a system rules can operate in forward or backward chaining. Forward chaining matches rules against facts to establish new facts. In backward chaining, the system starts with what it wants to prove and tries to establish the facts it needs to prove it.

Frames, another knowledge-representation scheme, are structural models for representing stereotyped objects or situations (MINSKY 1975). A class frame is a collection of all information that describes a class of objects. An object or instance frame is a collection of all information that describes an individual of a class frame. Each frame has slots that contain properties and relations about classes and objects. The slots specify, through an associated set of rules or procedures, what is known about an object and how can be acquired. Inexact reasoning procedures have been developed to complement the knowledge representation and inferencing mechanisms of rule and frame-based systems in cases where facts, rules and, consequently, conclusions are uncertain or inexact. These techniques represent uncertainties in facts, combination of facts, rules of inferencing, and facts supported independently by several rules (HARMON & KING 1985, JACKSON 1986).

3.3 *Hypermedia*

Hypermedia systems represent, organize, and display information around a hierarchy or network of multiple connected nodes. The linked nodes can be textual, graphic, photographic, audio, full motion video, and animation. A hypermedia system presents several options to its users, who determine which ones to follow at the time of reading. This structure allows users to jump easily from one topic to related or supplementary material and thus link diverse information rapidly and by association, much as a human being accesses related information (PARSAYE et al. 1989, BIELAWSKI & LEWAND 1990, NIELSEN 1990).

The basic architectural element of a hypermedia system is evident in the metaphor of the familiar 3×5-inch card used for keeping notes. Hypermedia partition knowledge into cards, representing the knowledge content as a chunk (e.g. conceptual unit) of text, graphics, sound, or video and into links, representing associations and relations among the cards – the structure of our knowledge. The result is a hierarchy or network of linkages among knowledge units. In Apple Macintosh's Hypercard, a card is the basic unit of information and links are pointers from one card, the departure card, to another card, the destination card (HyperCard Stack Design Guidelines 1989). A collection of cards is called a stack. Cards consist of text fields, graphics, video, sound and buttons providing the links to other cards and stacks. Links are implemented in Hypercard by constructing anchors on the card and then associating a HyperTalk language script with them. Anchors, or hot spots, can be either words, text strings, buttons, or graphics. The hypermedia structure forms a network of cards and links. Moving around this network is referred to as browsing or navigating, rather than just "reading," to emphasize that users must actively determine the order in which they read the cards (NIELSEN 1990).

4 *Applications of structural methods to terrain analysis*

4.1 *Structural pattern-recognition of drainage patterns*

Drainage pattern is the configuration, or shape, of a set of tributaries within a drainage network. Most research on drainage networks has focused on their topologic aspects and the DEM-to-watershed transformation, while limited work has been reported on the numerical classification and identification of the drainage patterns (PIKE 1993). Empirical descriptions of more than thirty patterns were discussed by HOWARD (1967), and DEFFONTAINES & CHOROWICZ (1991). ARGIALAS et al. (1988) developed a prototype software system to identify drainage patterns by a structural pattern-recognition approach. This entails the design of conceptual drainage pattern models, and their corresponding numerical hierarchical and relational models, selection and extraction of pattern attributes, and design of a classification strategy. Patterns are described and classified by modeling their topologic, geometric, and structural relationships among constituent streams. Eight drainage pattern types were selected and quantitatively described and classified: dendritic, pinnate, parallel, trellis, rectangular, angular, radial, and annular.

The structural models represent drainage patterns in terms of their constituent objects, object attributes and relationships. Object and attribute selection were based on the knowledge, structure and constraints of patterns embedded in their empirical descriptions. For example:

- The dendritic pattern is a treelike branching system where tributaries join a gently curving mainstream at acute angles.
- The trellis pattern contains primary tributaries that are long, straight, and parallel, but perpendicular to the main stream. Secondary tributaries are numerous, short, perpendicular to the primary ones, parallel to the main stream, and essentially the same size.

According to these, and other, similar descriptions, a drainage pattern can be identified by recognizing that (1) it is composed of a main stream, from which issue primary tributaries, and from them secondary tributaries; and (2) it is characterized by certain attributes of and relationships among the main stream, and primary and secondary tributaries. The main stream and the primary and secondary tributaries are termed the trunk, branches, and leaves, respectively. Collectively they are semantic objects, because they express the components of the patterns according to their descriptions. The semantic objects, their attributes, and their interrelationships constitute the "stereotype" structural drainage pattern model. Table 3 shows the structural models for representing the dendritic, pinnate, rectangular, and angular patterns and Table 4 shows typical computed attributes for these models.

The semantic objects were defined, through a drainage pattern hierarchy, by employing Strahler segments, reaches, and nodes (Fig. 1). The semantic objects were decomposed into Strahler segments (SS) of three orders (STRAHLER 1964). The Strahler segments were decomposed into reaches and the reaches were defined by their nodes. The procedure for generating the hierarchical model started at the bottom of the hierarchy. Nodes were aggregated to reaches, reaches to Strahler segments, and Strahler segments to semantic objects. An attribute list was designed and attached to each node of the object hierarchy, in the form of a relational table, to characterize the object of that node.

Drainage pattern attributes were designed to describe: (1) the semantic objects and their attributes (e.g., elongation of branches, straightness of trunk, uniformity of leaves), (2) the object relationships (e.g., perpendicularity, bifurcation ratio), (3) the overall pattern (e.g., average of all junction angles), and (4) all the intermediate objects, such as nodes, reaches, Strahler segments, junction nodes, intermediate nodes and others (Table 3). Attribute extraction involved computing attributes of drainage pattern models from information stored in the hierarchical and relational models. Although the computed attributes are numerical-valued, they have been converted to

Table 3. Structural models for representing dendritic, pinnate, rectangular, and angular drainage by pattern recognition with the DPA system (see Table 4).

Object or Relation	Attributes	Attribute values for Dendritic	Pinnate	Rectangular	Angular
Object trunk	TSHAPE	STRAIGHT	STRAIGHT	STRAIGHT	STRAIGHT
	BRTYPE	TWOSIDED	TWOSIDED	TWOSIDED	TWOSIDED
	MAOT	OBTUSE	OBTUSE	RIGHT	NA
Object branch	BSHAPE	NA	STRAIGHT	NA	NA
	BRELON	SHORT	MEDIUM, LONG	NA	NA
	MAOB	OBTUSE	OBTUSE	RIGHT	NA
Object leaf	UNLEAF	NA	NA	NONUNIFORM	NA
	MAOL		NA	RIGHT	NA
Trunk-branch relations	MATB	ACUTE	ACUTE	RIGHT	NA
Branch-leaf relations	RBRBL	SMALL, MEDIUM, LARGE	LARGE	SMALL, MEDIUM	NA
	BLAZDIF	NA	NA	NA	NA
	MABL	ACUTE	NA	RIGHT OR ACUTE	NA
	RMA12	NA	NA	NA	NA
Trunk-leaf relations	None	NA	NA	NA	NA
Leaf-leaf relations	MALL	ACUTE RIGHT	ACUTE	RIGHT	NA
Overall pattern	RJAW	ACUTE, SACUTE	ACUTE SACUTE	RIGHT	RIGHT
	RANMT	LARGE	LARGE	LARGE	LARGE

Table 4. Typical attributes computed for the drainage pattern models with the DPA system (see Table 3).

Attribute Symbol in FORTRAN	Explanation of attribute
TSHAPE	Shape of the trunk
BRTYPE	Type of Branching
MAOT	Mean intermediate angle on the trunk
BSHAPE	Branch shape
BRELON	Branch elongation
MAOB	Mean intermediate angle on the branches
UNLEAF	Uniformity of leaves
MAOL	Mean intermediate angle on the leaves
MATB	Mean junction angle between the trunk and branches
RBRBL	Ranked bifurcation ratio between branches and leaves
BLAZDIF	Azimuthal difference between branches and leaves
MABL	Mean junction angle between the branches and leaves
MALL	Mean junction angle among leaves
RJAW	Ranked junction angle
RANMT	Ranked angle with vertex at the center of gravity of the nodes and sides diverging to the mouth of the pattern and to its most distant node

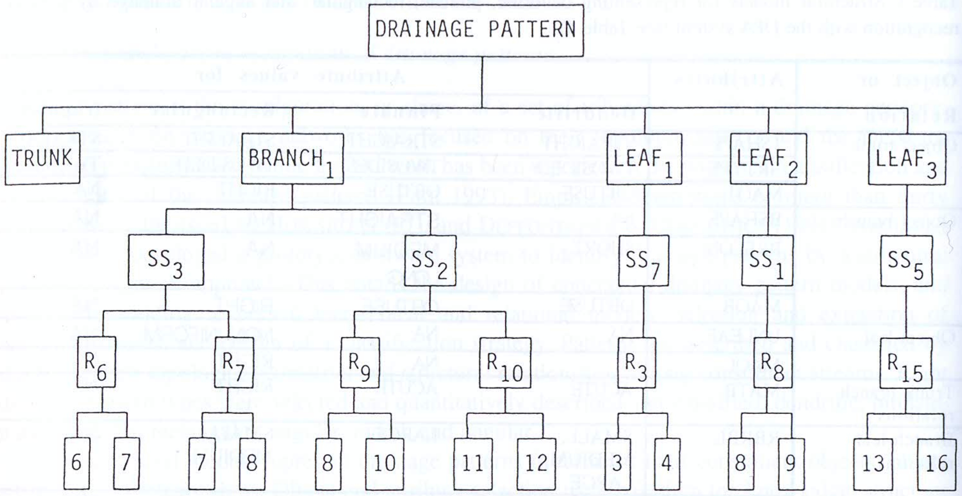

Fig. 1. Example of the hierarchical organization of the objects of a drainage pattern in the DPA system. SS_1 implies a Strahler segment, R_6 implies a reach, and plain numbers, like 6 or 7, imply nodes. Trunk, branch, and leaf are the semantic objects (see text).

discrete-valued (symbolic) attributes, through appropriate thresholds, to agree with the linguistic terminology of the patterns definitions. One of these is described as follows:

BRELON is defined as the ratio of the mean length of branches to the mean length of leaves (RMLRBL) in three classes: SHORT (RMLRBL < 3.5), MEDIUM (3.5 < RMLRBL < 4.8), LONG (RMLRBL > 4.8). BRELON is a geometric attribute that expresses the elongation of the branches of a drainage pattern. The shorter the leaves are in relation to the branches, the larger BRELON will be. BRELON characterizes the length of the branches in a manner invariant of pattern scale. BRELON is expected to be MEDIUM to LONG for the trellis and pinnate patterns. The critical values of 3.5 and 4.8 for RMLRBL were chosen according to empirical observations.

A decision tree has been designed for the classification of drainage patterns. The nodes of the decision tree were composed of groups of tests. The tests evaluate the presence or absence of certain combinations of attributes and values and thus enable the establishment or rejection of a decision at each node of the tree. Based on the outcome of these tests, each pattern was assigned to one of the eight predetermined classes. Fig. 2 shows the group of tests used to identify dendritic, pinnate, rectangular, and angular patterns. Depending on the attributes used for the classification, the decision was labeled "likely" or "definitely" so.

The method was programmed as the Drainage Pattern Analysis (DPA) system. To verify the method and its capability, the DPA system has been evaluated for twenty test patterns, both real and artificial, representing the eight major drainage classes. The DPA system recognized all twenty test patterns. Fig. 3 shows the results for dendritic, pinnate, rectangular, and angular patterns. It is concluded that pattern recognition provides a formal framework for describing the structure of drainage patterns. Further work on an expert-system approach for representing the photo-interpretation logic for drainage patterns was presented recently by HADIPRIONO et al. (1990) and ICHOKU & CHOROWICZ (1994).

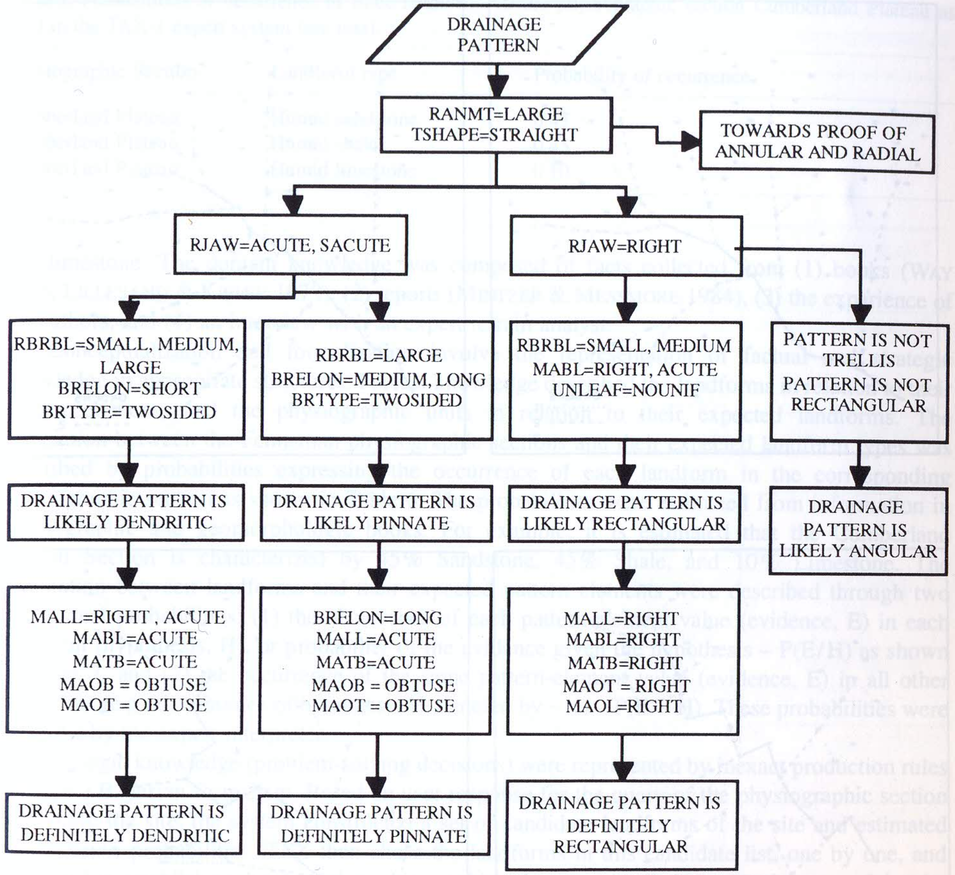

Fig. 2. Group of tests, embedded in a decision tree, needed to classify dendritic, pinnate, rectangular and angular patterns with the DPA system (see Tables 3, 4, Fig. 3).

4.2 *Knowledge-based expert systems for landform interpretation*

The expert-system approach to terrain-analysis problem-solving was implemented in a rule-based language involving inexact reasoning (ARGIALAS & NARASIMHAN 1988a and 1988b). Subsequent work added such knowledge-representation formalisms as frames (ARGIALAS 1989) and fuzzy sets (NARASIMHAN & ARGIALAS 1989). The Terrain Analysis eXpert (TAX-1, 2, 3) systems are described here (Table 5). The approach for building the Terrain Analysis eXpert (TAX-1) system involved development of five interdependent and overlapping tasks (ARGIALAS & NARASHIMHAN 1988a, 1988b): (1) Identification, (2) Conceptualization, (3) Formalization, (4) Implementation, and (5) Testing and evaluation.

Identification pertains to data, hypothesis, goals, and reasoning tasks of TAX. The goal of a typical consulting session with TAX was to infer the landform type of a site. Only one landform type was assumed to exist on a stereopair of aerial photographs. The landform pattern-element approach, described earlier, was implemented. Six landform types were chosen to focus the knowledge-representation process. These types were the humid and arid forms of sandstone, s

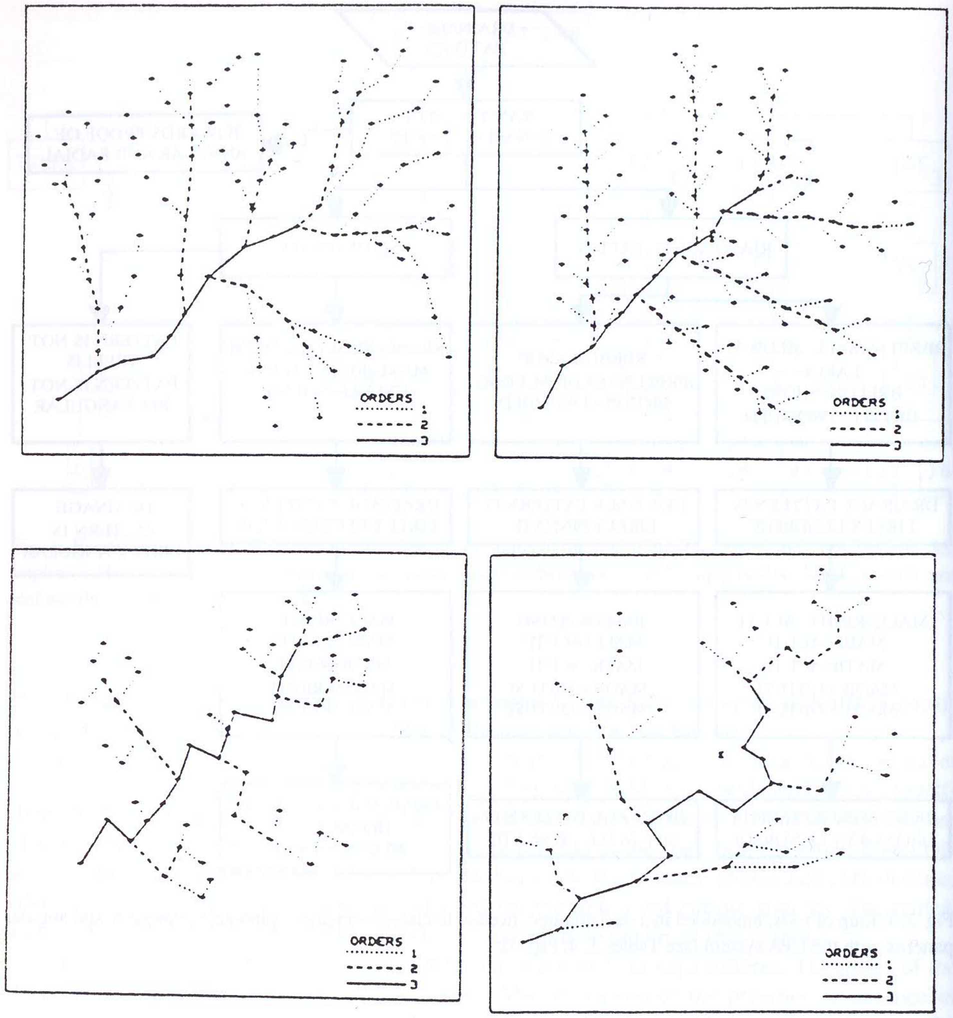

Fig. 3. Classification of drainage patterns by structural pattern recognition. Clockwise from upper left the patterns have been recognized as dendrictic, pinnate, rectangular, and angular (see Tables 3, 4, Fig. 2).

Table 5. Comparative features of the three terrain analysis expert-system prototypes.

Feature of prototype	TAX-1	TAX-2	TAX-3
Object representation	Object-attribute-value	Frames	Frames, objects
Inference	Production rules	Rules	Rules, demons
Inexact reasoning	Bayesian	Bayesian	Fuzzy sets
Rule chaining	Forward	Backward/forward	Backward/forward
Expert system tool	OPS5	INTELLIGENT COMPILER	KEE

Table 6. Probabilities of occurrence of three landforms in the physiographic section Cumberland Plateau as used in the TAX-1 expert system (see text).

Physiographic Section	Landform type	Probability of occurrence
Cumberland Plateau	Humid sandstone	0.45
Cumberland Plateau	Humid shale	0.45
Cumberland Plateau	Humid limestone	0.10

and limestone. The domain knowledge was composed of facts collected from (1) books (WAY 1978, LILLESAND & KIEFER 1979), (2) reports (MINTZER & MESSMORE 1984), (3) the experience of the authors, and (4) an interview with an expert terrain analyst.

Conceptualization and formalization involve the representation of factual and strategic knowledge in appropriate structures. Factual knowledge described the landforms in relation to their pattern elements and the physiographic units in relation to their expected landforms. The association between the Fenneman physiographic sections and their expected landform types was described by probabilities expressing the occurrence of each landform in the corresponding physiographic section as shown in Table 6. The probabilities were estimated from information in physiographic and geomorphologic books. For example, it is estimated that the Cumberland Plateau Section is characterized by 45% Sandstone, 45% Shale, and 10% Limestone. The association between landforms and their expected pattern elements were described through two conditional probabilities: (1) the occurrence of each pattern-element value (evidence, E) in each landform (hypothesis, H), or probability of the evidence given the hypothesis – P(E/H) as shown in Table 7, and (2) the occurrence of the same pattern-element value (evidence, E) in all other landforms (e.g., the absence of hypothesis H, denoted by ~H) – P(E/~H). These probabilities were provided by the expert interpreter.

Strategic knowledge (problem-solving decisions) were represented by inexact production rules through a Bayesian formalism. Based on user response for the query of the physiographic section containing the site, the system constructed a set of candidate landforms of the site and estimated their a priori probabilities. TAX then chose the landforms in this candidate list, one by one, and attempted to establish each one of them, by matching the user-supplied pattern-elements of the site with those expected. This was achieved with the design of rules linking observed evidence of pattern elements (E) with landform hypotheses (H), implied by the evidence. A generic form of the rule is:

IF E THEN H (to degree) LS, LN.

This means that evidence E suggests the hypothesis H to a degree specified by the certainty factors LS and LN. The number LS indicates how encouraging it is to our belief in the hypothesis to find the evidence present, while LN indicates how discouraging it is to find the evidence absent. LS and LN aren't the only certainty factors in TAX-1. The two meausres LS and LN were computed as a function of the conditional probabilities P(E/H) and P(E/~H) provided by the expert. Each piece of evidence and each hypothesis in the system has its own certainty factor P, standing for the probability that the evidence is present or the hypothesis is valid.

TAX-1 also maps the subjective expression of certainty (C) of the user supplied pattern-element values onto a scale that ranges from –3 (certain it's absent) to +3 (certain it's present). In the case the number chosen is 2 (somewhat certain it's present), the system uses the number 2 to adjust the probability of all pertinent landform hypotheses. Since 2 is greater than 0, the pertinent landform probabilities would be adjusted upward. Changing the certainty of pattern elements causes a change in the probability of landform hypotheses. This probability propagation occurs automatically in TAX-1 whenever the user inputs a new pattern element value. The propagation

Table 7. Probabilities of occurrence of each pattern element value (evidence) in each of three landforms (hypotheses) provided by an expert interpreter and used in the TAX-1 expert system (see text).

Pattern element	Pattern element value (Evidence)	P (Evidence/Hypothesis) Conditional probability of each evidence given the hypothesis of: Humid Sandstone	Humid Shale	Humid Limestone
Topography	Steep slopes	0.6	0.15	0.5
	Medium slopes	0.2	0.7	0.25
	Flat-undulating	0.2	0.15	0.25
Drainage pattern	Dendritic	0.6	0.8	0.1
	Rectangular	0.2	0.1	0.0
	Angular	0.2	0.1	0.1
	Internal	0.0	0.0	0.8
Drainage texture	Coarse	0.6	0.1	0.1
	Medium	0.3	0.3	0.0
	Fine	0.1	0.6	0.0
Soil tone	Light	0.7	0.2	0.3
	Medium	0.2	0.6	0.5
	Dark	0.1	0.2	0.2
Landuse-valleys	Cultivated	0.3	0.7	0.8
	Forested	0.5	0.1	0.1
	Urban	0.2	0.2	0.1
Landuse-slopes	Cultivated	0.1	0.1	0.7
	Forested	0.9	0.8	0.2
	Urban	0.0	0.1	0.1
Gully type	V-shaped	0.8	0.1	0.5
	Sag and swale	0.1	0.8	0.0
	U-shaped	0.1	0.1	0.5
Gully amount	None	0.3	0.0	0.8
	Few	0.7	0.2	0.2
	Many	0.0	0.8	0.0

continues all the way to the top nodes, changing the probabilities of the goal hypotheses which is the landform of the site. The rules in TAX form an inference net, which indicates all the connections between evidence and hypotheses and hence all the possible inference chains that could be generated from the rules.

Using the certainty value C, the previous rule takes the form (shown here for the evidence = topography and the hypothesis = sandstone):

IF the topography of the site is steep slopes, with certainty C (steep slopes) and the current hypothesis for the landform of the site is sandstone, with certainty C(sandstone)

THEN modify the certainty C(sandstone) by taking to account C(steep slopes), C(sandstone), LS for steep slopes, and LN for steep slopes.

TAX employed such rules for all pattern elements and for all hypothesized landforms. The landform which had the highest a posteriori certainty associated with it was then declared to be the landform of the site.

Implementation provides the programming of the formalized representation in an expert-system tool. The key landform-related objects and decision rules were implemented within the OPS5 language (ARGIALAS & NARASIMHAN 1988b). TAX's production system model consists of a

Table 8. Typical landform-related objects with their attributes and values designed for the TAX-1 expert system shown coded in the OPS5 language and explained in English. Objects are shown boldface, attributes are preceeded by a caret, and values are shown in italics.

Object	Attribute	Value
landform topography pair		
	^landform_type	*sandstone humid*
	^topography	*steep slopes*
	^landform_topography_peh	*0.60*
	^landform_topography_penoth	*0.0*
	^status	*nil*

This object was designed to express the relation between any landform and its topography. This instance of this object indicates that landform "sandstone_humid" has topography "steep_slopes" with probability - P(E/H)=0.6 (see Table 7) and it has not been used for reasoning as yet by TAX (status=nil).

Object	Attribute	Value
landform_of_the_site		
	^landform_type	*sandstone humid*
	^probability	*0.45*
	^status	*nil*

This object was designed to store the *a priori* or *a posteriori* probability of any landform of the site. The initial value, here set to 0.45, is obtained from *a priori* knolwedge regarding the site (see Table 6). This instance of this object indicates that landform "sandstone_humid" has *a priori* probability - P(H)=0.45 and it has not been used for reasoning as yet by TAX (status=nil).

Object	Attribute	Value
topography_of_the_site		
	^landform_type	*sandstone humid*
	^topography	*steep slopes*
	^certainty_value_of_topography	*+1*
	^status	*nil*

This object was designed to store the topography of the site and its certainty - as these are provided by the user. This instance of this object indicates that topography "steep_slopes" was observed by the user with certainty +1 and landform "sandstone_humid" is one of the canditate landforms with such topography. Similar objects will also be created for all other landforms of the knowledge base which are known to have topography "steep_slopes".

knowledge base and an inference engine (Fig. 4). The inference engine matched, selected, and executed rules. The knowledge base was composed of facts and rules and it constituted the OPS5 program code. TAX's knowledge base repreented facts and inexact decision rules. Table 8 shows typical facts represented through object-attribute-value triplets in the OPS5 language accompanied by proper explanation. Production rules, written in OPS5, are represented by condition-action pairs. Each rule has a condition part which was composed of a conjunction of one or more antecedent clauses, and an action part, the consequent, which created or modified working memory elements. Both the antecedent and consequent parts are logical combination of clauses, the antecedent part specifying the preconditions, and the consequent part specifying a set of actions modifying the working memory by adding, deleting, or changing facts. Table 9 shows, in OPS5 code and in English, the rule that, for a given physiographic section, searches the knowledge base for information about the probable landforms. If such information is resident in the working memory – by an answer of the user to a previous query – the rule updates the prior probability of the

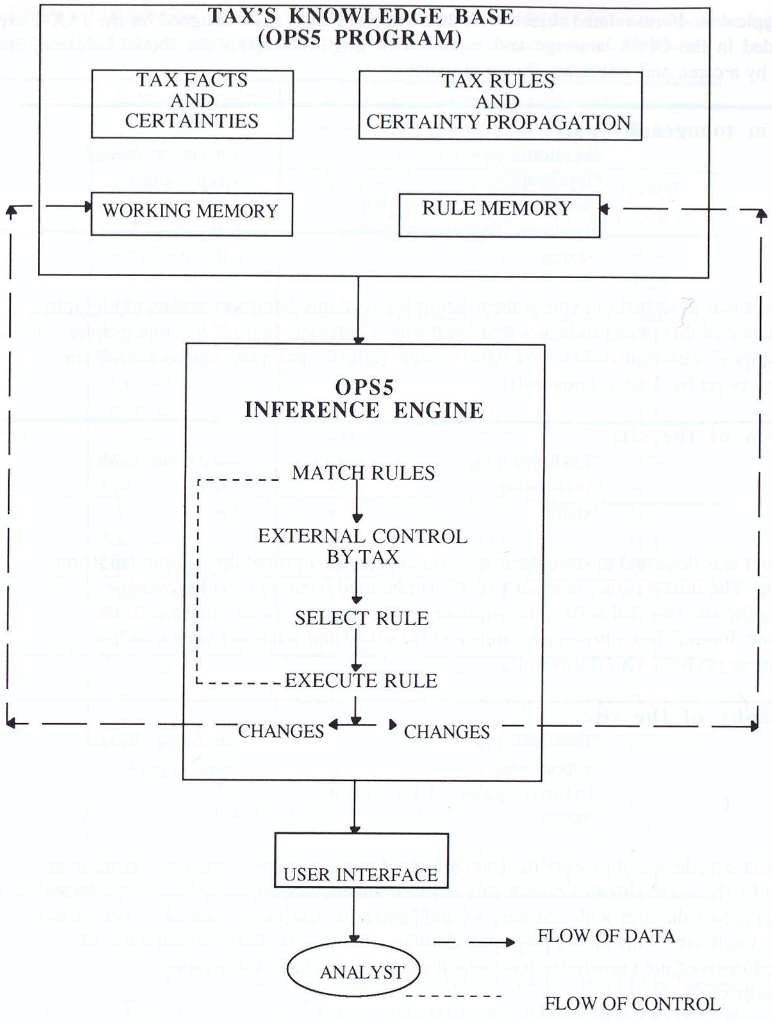

Fig. 4. The production system architecture of TAX-1, an expert system for terrain analysis.

landform of the site to the probability of the landform associated with the given physiographic section.

Five analysts at various levels of experience were asked to evaluate the system by observing a given site of a humid sandstone on a stereopair of aerial images and responding to the queries of TAX (Table 10). The evaluation of TAX was successful in the sense that (1) the knowledge-representation scheme was judged adequate although improvements are needed, (2) TAX correctly inferred the correct landform for all analysts and for the right reason, (3) the embedded knowledge seems to be consistent with the expert's knowledge although further experiments with other formalisms are needed.

A second prototype, the Terrain Analysis Expert-2 (TAX-2) system (ARGIALAS 1989) was designed in the Intelligence Compiler, a frame and rule based expert-system tool (Intelligence Ware 1986). Table 5 shows the comparative features of the three implementations of TAX-1, -2, -3.

Table 9. Rule that hypothesizes a landform type based on physiographic information designed for the TAX-expert system shown coded in the OPS5 language and explained in English (see text).

OPS5 coded rule	(p hypothesize_a_landform_type_based_on_physiogrphy	
		(section_landform_pair ^section_name <section_value> ^landform_type <landform_value> ^section_landform_prob <probability_value>)
	->	
		(make landform_of_the_site ^landform_type <landform_value> ^probability <probability_value>))
Explanation of OPS5 language symbols	p	means that what follows is a production rule
	^	implies that what follows is an attribute name
	<>	encloses an attribute value
	->	means "then"
English version of above rule	If	there exists a landform type in the knowledge base which occurs in the same physiographic section as the one given by the user,
	then	create an object landform-of-the-site and initialize its probability to the a priori probability of the occurrence of that landform type in that physiographic section

Table 10. A typical consultation script generated with the terrain analysis expert system TAX-1. Underscored ar boldfaced numbers indicate the user's certainty, between -3, 3, for the presence of the specific pattern-eleme value in the study area.

Please provide the following information about the site.
To which Physiographic-section does the site belong?
Cumberland-plateau
Is the "gully-amount" of the site "none" ? **-3**
Is the "gully-amount" of the site "few" ? **1**
Is the "gully-type" of the site "v-shaped" ? **3**
Is the "landuse-valleys" of the site "cultivated" ? **-1**
Is the "landuse-valleys" of the site "forested" ? **3**
Is the "landuse-slopes" of the site "cultivated" ? **-3**
Is the "landuse-slopes" of the site "forested" ? **3**
Is the "soil-tone" of the site "medium" ? **1**
Is the "soil-tone" of the site "light" ? **0**
Is the "soil-tone" of the site "dark" ? **0**
Is the "drainage-texture" of the site "coarse" ? **3**
Is the "drainage-type" of the site "internal" ? **-2**
Is the "drainage-type" of the site "angular" ? **2**
Is the "topography" of the site "steep-slopes" ? **3**
Is the "gully-amount" of the site "many" ? **-2**
The site appears to be "sandstone-humid"
The certainty associated with this result is "0.99"

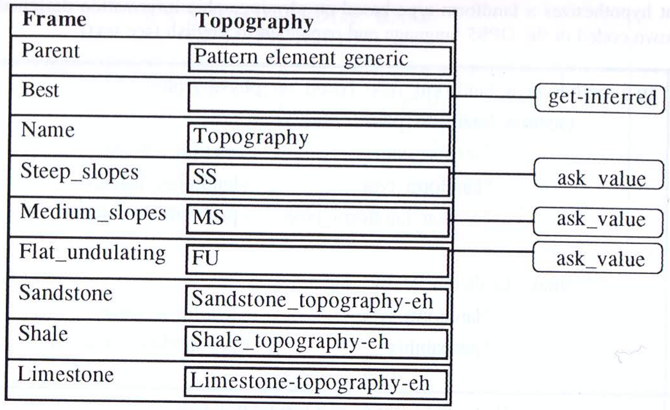

Fig. 5. Typical frame for topography in expert system TAX-2 (see text).

TAX-2 demonstrates the representation and reasoning capabilities of frames, backward and forward chaining rules, and inexact reasoning for the landform interpretation. Frames were developed to represent relations between physiographic sections and landforms, landforms and their pattern elements, and pattern elements and their associated likelihood of occurrence in each landform type. Frames demonstrated the inheritance of attributes from generic representations of terrain units to their specific instances. Frames also represented procedural knowledge by embedding it in the form of active values or attached predicates. Fig. 5 shows a typical frame for topography. It is indicated, through the property parent, that frame topography is a child of frame pattern-element-generic. Topography has been designed with ten slots (properties), some declare possible values (e.g., steep-slopes, medium-slopes, and flat-undulating), others declare default assignments (e.g., name), while others contain specific values or have attached predicates for computation of values (e.g., best). Property best has a procedural attachment, e.g. predicate get-inferred, which will call the corresponding backward rule.

A third prototype, the Terrain Analysis Expert-3 (TAX-3) system (Table 5) used fuzzy set theory to represent the imprecision that is inherent in the qualitative descriptions of terrain terms (NARASIMHAN & ARGIALAS 1988b, NARASIMHAN & ARGIALAS 1989). Fuzzy set approaches, pioneered by ZADEH (1983) provide a way for dealing with vague linguistic descriptions such as "gentle relief", and "partly dendritic, partly rectangular drainage pattern".

A label such as "tall" (for mountain) may be construed as a fuzzy restriction on the values of the underlying numerical variable, in this case the height in feet of a mountain. This numerical variable is also called the base variable of the fuzzy set. A fuzzy restriction on the values of the base variable is characterized by a compatibility or membership function, which associates with each value of the base variable a number in the interval [0,1]. The membership function of objects in such a fuzzy set can range from 0, complete incompatibility with the constraints, to 1, total satisfaction of the constraints. A simple example is given here for relief. Local relief is defined as the difference in elevation between the highest and lowest points in an area. Local relief of a landscape is usually expressed using terms such as Gentle, Moderate and Strong. Typical range of values used by experts, for these classes of Relief are: Gentle Relief: 0–100 m, Moderate Relief: 100 to 300 m, and Strong Relief: greater than 300 m.

For relief there is a well-defined continuous numeric base variable "Relief in feet". A linguistic label such as Gentle Relief may be construed as a fuzzy restriction on the values of the base variable "Relief in feet". From the above definitions, we can see that a flat plain or a site having a

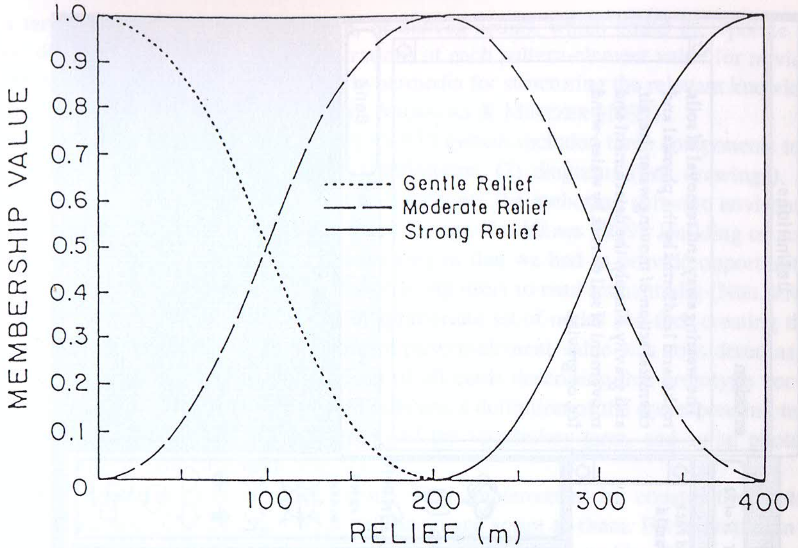

Fig. 6. Membership functions for topographic relief in expert system TAX-3 (see text).

Relief of 0 m would be definitely called Gentle Relief, that is, the membership of 0 m in Gentle Relief would be 1 (Fig. 6). A Relief of 100 m could be called Gentle or Moderate, that is, the membership value in Gentle Relief would be 0.5 and the membership value in Moderate Relief would be 0.5. The membership value in Gentle Relief decreases from 1 to 0, as the Relief increases and becomes 0 when Relief equals 200 m. The membership value in Moderate Relief is maximum, that is, 1, when Relief equals 200 m. The membership value in Moderate Relief decreases as the value of Relief goes farther from 200 m on either side. When Relief equals 100 m, the membership in Gentle Relief is 0.5 and so is the membership in Moderate Relief. The characteristics of Strong Relief are the reverse of Gentle Relief. The membership value in Strong Relief is 0 when Relief is 200 m. From there onwards, the membership in Strong Relief increases as Relief increases. The membership is equal to 0.5 when Relief is 300 m and reaches a maximum value of 1, when Relief is greater than or equal to 400 m. The membership functions given graphically in Fig. 6 have been adopted to represent the three relief classes. The definition of relief classes in terms of the parameters of their membership functions have been given by NARASIMHAN & ARGIALAS (1989).

4.3 *The visual vocabulary: a hypermedia system for terrain-related terms*

The expert systems (TAX-1, 2, 3) assume that their users clearly understand each of the visual pattern-elements they need to provide to the system queries in order to infer the landform at a site (Table 1). While this may be a fair assumption for an analyst of average experience, it is not for a novice user, owing to the complexity of the knowledge base. The TAX knowledge bases described earlier use seven pattern-elements, each of which may have multiple values (Table 1). For the most rudimentary knowledge base, the user must be familiar with more than a hundred different pattern-element values. Many more terrain features are needed for knowledge bases of significant size and detail (HOFFMAN & PIKE, in press). A novice user is unlikely to have unambiguous mental and visual models of all these pattern elements. Accordingly, an interactive computer system could

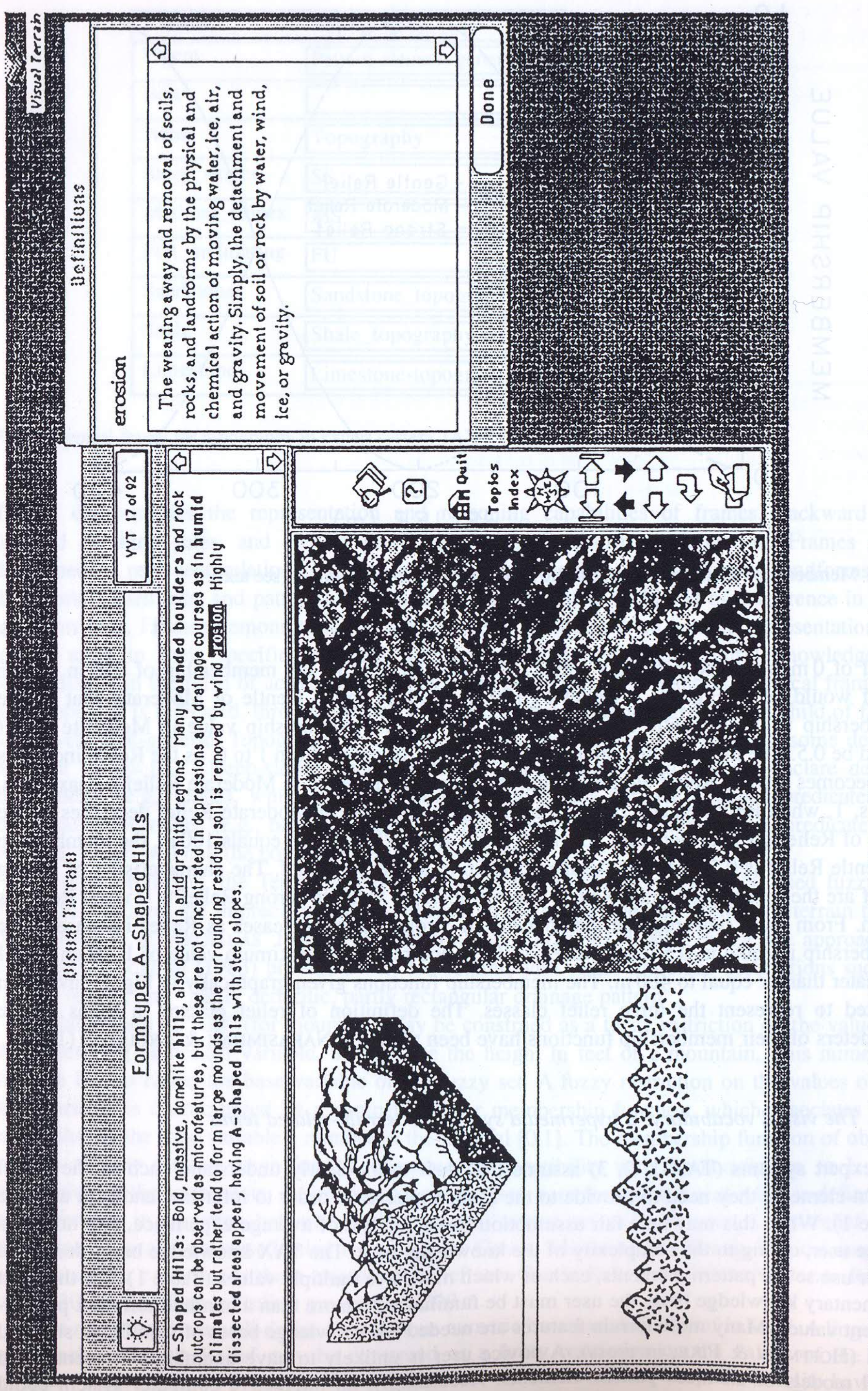

Fig. 7. Typical Hypercard card used to represent the terms of the Terrain Visual Vocabulary, with a smaller, user-invoked card explaining a particular unknown concept of the first card.

provide a terrain visual vocabulary (lexicon, or encyclopedia), which could incorporate explicit definitions, diagrams and photographic illustrations of each pattern-element value for novice users of expert systems like TAX. The potential of hypermedia for structuring the relevant knowledge for teaching image interpretation was described in ARGIALAS & MINTZER (1992).

The prototype Terrain Visual Vocabulary (VVT) system included three components to define and graphically depict landform features: (1) definitions, (2) diagrams (line drawings), and (3) scanned aerial images. The system was built in Hypercard, the authoring software environment of the Apple Macintosh computer (HyperCard Stack Design Guidelines 1989). Building or authoring the VVT system differed from regular text authoring in that we had to provide opportunities and priorities for knowledge exploration instead of ordering users to read sequentially (NIELSEN 1990). This was accomplished by first establishing an appropriate set of nodes and then creating the links between these nodes. In the VVT, each landform pattern-element value was considered as a node and was represented by a card (Fig. 7). The set of all cards describing this prototype vocabulary was stored in one HyperCard stack. Each card contains a definition of the corresponding term in a text field, diagrams (profile and block diagram) of the vocabulary term, and aerial photographs exemplifying landforms for each term (Fig. 7).

The links between associated ideas (terms) were implemented by constructing buttons or anchors and then associating a certain Hypertalk language script to them. For example, in Fig. 7, all boldface words in the definition field are anchors that can be activated by clicking the mouse on them and thus transferring control to the card describing them. Another set of anchors was designed to provide for further definition of certain terms which were not themselves pattern-element values. These are indicated by underscoring the term. By clicking in one of these anchors, control was transferred to the additional "dictionary" like stack as shown in Fig. 7 for the example on the term "erosion". Besides this non sequential, non linear jump, there is a provision for sequential browsing of the vocabulary terms. Arrow buttons at the right side of the card provide for such navigation to the next and previous card (term). One may also choose to jump to the beginning or to the end of the stack or to move from one of the pattern-elements to the next, e.g., from topographic form to drainage pattern. With the help of these links the user can interactively and non-sequentially access and display the visual vocabulary terms and thus effectively explore the knowledge structure embedded through the links and cards. The VVT also offers users not only a single piece of explanatory text or a visual aid, but also a doorway into the entire body of photointerpretation knowledge through links active from that particular node.

5 *Discussion – Mutual and unifying aspects*

The three seemingly distinct methods applied to landforms and their pattern elements share five aspects (Table 2):

1. Domain specific knowledge (terrain-analysis expertise) uncovers the structure of each entity – structure is in the eye of the percipient or domain expert.
2. Symbolic representation of the involved entities, objects, attributes, relations, associations, and inferences. Knowledge is symbolic and representational; "knowing" consists in large part of symbolically representing facts and procedures.
3. Factual knowledge is represented in small chunks (objects, hypermedia nodes, working memory facts). This process seems to mimic the way experts store and apply their knowledge – searching ghrough these chunks for a solution.
4. Representing the organizational structure of an entity by hierarchical and relational models, production rules, hypermedia links.
5. Searching for a certain configuration of entities (objekcts) satisfying particular relations in finding a solution (data-driven activation of production system, user-driven activation in a hyper-

media system). Problem solving entails searching for an answer in a space of possible problem states; a solution is found incrementally (one evidence at a time) and opportunistically (as an opportunity for completing an identification arises).

Structure is the characteristic common to all three methods: structural pattern-recognition, hypermedia, and knowledge-based systms. Structure may be defined as the configuration of elements, parts, or constituents in a complex entity or the interrelation of parts or the principle of organization in a complex entity. It is attributed by an expert to an arrangement of components in order to obtain more meaning than follows from simply an aggregation of the parts. While an image, landform, or abstract entity may have the potential for being regarded as having structure, an actual conception of that structure must be provided by an expert.

In all three approaches, the structural description of an entity is an organization of subentities (objects, nodes, facts) (Table 2). An organization is a complex of relations and associations that subsist between the entities that are to be learned, reasoned or recognized. In the DPA system, a hierarchical and relational approach expressed the organization of the drainage network. In the TAX systems, object, attribute, values (and frames) represented the landform-pattern element organization. In the VVT system, the interconnected cards expressed the structure subsisting between the terrain-related terms.

To learn about, reason with, or recognize an entity, each method searched for a solution or match in a space of possible problem states to find if a particular organization exists, that is, search for the desired configuration of subentities satisfying particular relations (Table 2). In the DPA system this search took place by the decision tree. In the TAX system, search took place by the inference engine employing the designed evidence-to-hypothesis rules. In the VVT, the hypermedia space was explored by a non-sequential, user activated control.

6 *Prospect*

The Drainage Pattern Analysis (DPA) system, the Terrain Analysis Expert (TAX-1, -2, -3), and the Terrain Visual Vocabulary (VVT) developed structures for representation and identification of terrain related objects. While these research prototypes are incomplete they provide a starting point for the systematic presentation, description, and identification of terrain-related objects through objective, formal and repeatable processes based on the concept of landform. Experience with other knowledge-representation paradigms and a more detailed and explicit formalization of the terrain-analysis process will be required to further these approaches. Morphometric attributes and their integration with digital elevation models and knowledge-based Geographic Information Systems (GIS) will greatly assist this effort. The methods described could also be applied to maps of slopes, relief, aspect, etc. and as such they do have direct application to morphometry.

Structural drainage-pattern models need to be extended and integrated with additional morphometric attributes and landform-related expert-systems. Further work is required to

1. extend this approach to additional drainage-pattern types,
2. integrate the present system with a network extraction system, based on the digital elevation model DEM-to-watershed transformation (BAND 1986, CHOROWICZ et al. 1992, ICHOKU & CHOROWICZ 1994).
3. expand present drainage-pattern attributes with additional 3-D morphometric attributes from the DEM (EVANS 1972, 1980, PIKE 1988a, 1988b and DIKAU 1989, 1990), and
4. integrate drainage recognition with the terrain-analysis expert-system to mutually support both capabilities.

Additional background or auxiliary information, including existing maps, is often required during landform interpretation. TAX has demonstrated the use of a priori physiographic information for focusing the search for the identification of the landform of a site. The expert analyst would better take into account the physiographic context, the regional context, the geomorphic process and other information to arrive at a diagnosis of the landform. With such "deeper knowledge" taken into acount, the landform identification process could reason much beyond the pattern elements alone. The following types of background or auxiliary information should be therefore acquired, represented and employed in computing the a priori probability of the site landforms. This might include regional geologic setting, structural and tectonic geology, soil data, and relevant cultural knowledge (e.g., cemeteries are often on elevated gravel). Such general information would reduce the search space and impose an establish-refine paradigm to problem solving.

There is a need to experiment with new schemes of terrain conceptualization. TAX was based on the landform pattern-element approach and Bayesian decision making. The pattern-element approach was developed to make the terrain-analysis process specific, well-documented, and systematic. The traditional pattern elements, however, only hint at what the expert perceives (HOFFMAN 1987). Therefore, using pattern elements for identifying the landform is a "zero order approximation" to how experts work during landform identification and as such it is limited. It has contributed to the first-generation prototype expert-systems for terrain analysis. To build the next generation of systems it is necessary to create new conceptualization schemes to more explicitly represent the knowledge of expert analysts. However, there are difficulties in eliciting such knowledge and at best it will come about through an incremental and iterative process (HOFFMAN 1987).

TAX was designed based on a Bayesian decision network created through forward- and backward-chaining inference engines coupled with objects or frames. It is unfair to assume that humans think (only) in terms of probabilities, certainties or membership functions. The hiding of perceptual relativity in numbers is merely a brute force solution to the tough problem of perception. The systems may work (more or less well) but in some sense, it washes the "meaning" away (HOFFMAN 1987). One has to uncover the knowledge hiden beneath the probabilities and certainties during reasoning and make that knowledge explicit with rules etc. Experiments should be conducted with new knowledge-representation paradigms and expert-system tools. There are many knowledge-representation methods and tools on the market, each with different features and degree of sophistication, development, and support environment. There is no agreement, however, as to the strengths and weaknesses of these formalisms. Neither is there agreement as to which are best for which kinds of problems. All methods and tools lack a comprehensive theory which could guide the construction of an intelligent system. None of the knowledge-representation methods by itself can satisfy all the needs of structuring terrain knowledge. The process of knowledge structuring and representation in any of these tools is still an art and one needs to apply human problem-solving by trial-and-error in determining the utility of these methods and tools. Hence, landform related knowledge needs to be modeled through new representation paradigms and tools to learn more about the knowledge-engineering process applied to terrain analysis.

Major types of links or associations need to be identified and represented betwen terrain related objects. Most textbooks/manuals have extensive, often implicit implications, relationships and cross-references among photointerpretation objects, elements, clues, and methods – which can be used to identify proper links. Good links should provide the means of organizing information within the hypermedia framework in patterns that may not be immediately discernible to novices without the help of the navigational tools offered by the links. Indeed, good links could help to categorize terrain related concepts into semantically and perceptually related units which will be linked and accessed by association, much as a human does. The challenge in choosing nodes and links is to structure the terrain related knowledge to reflect the mental models that experts create when they reason about landforms (HOFFMAN & PIKE, in press).

Hypermedia can assist in developing terrain-analysis systems and integrating them with expert systems. The marriage of hypermedia and expert systems is inevitable for three reasons: (1) hypermedia can provide context-sensitive help for expert systems, (2) expert systems can provide the missing element of hypermedia e.g., procedural support, and (3) knowledge organization implemented in hypermedia systems can be used to initially conceptualize terrain-analysis knowledge which subsequently will be represented in an expert-system tool (ARGIALAS & MINTZER 1992). This can be achieved with the construction of semantic networks through the hypermedia links. Conceptual or organizational links relating semantically associated units can form semantic networks, that is, a graphical representation of objects or concepts formed into nodes that are linked together in an associative way (ARGIALAS & HARLOW 1990). Semantic networks are an expert-system representation method and, thus, establishing conceptual links between hypermedia nodes provides the basis for a subsequent representation in an expert-system environment.

Finally there is a need for integrating geometric, spectral, and semantic aspects of problem solving. The geometric signature proposed by PIKE (1988a and 1988b) involving geomorphometric attributes such as those developed by EVANS (1972 and 1980), and DIKAU (1989, 1990) could be integrated with the spectral signature employed in remote sensing and merge into a semantic signature composed of all entities, attributes, relationships and strategies needed to reason and to study geomorphologic models and theories.

From a practical point of view, the same approach can be extended to derive engineering properties of a site such as soil type, depth to water table, depth to bedrock, etc. It is anticipated that these engineering site-attributes could also be represented using an expert-system approach. The elements of such an expert system can be further synthesized to produce information on groundwater resources, engineering suitability, environmental impact assessment, the modelling of hazard and risk, and other objectives.

7 *Conclusions*

Experience has no substitute in terrain analysis, making this close relative of geomorphology particularly amenable to structural knowledge models (pattern recognition, expert systems, hypermedia). Structured models (1) facilitate retrieval of relevant imformation and convey the organization of associated ideas; (2) allow interactive and non-sequential location, browsing, and learning of concepts and processes; (3) make the landform-pattern element process more explicit, objective, repeatable, and rigorous; and (4) assist understanding of what characterizes terrain-related expertise and the landform interpretation process. This review has shown that structural knowledge models can bring to terrain analysis, and by inference geomorphology and geomorphometry the real possibility of accumulating and representing the knowledge of experts and making it available to others in a usable form.

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Morphometric landform analysis of New Mexico

by

RICHARD DIKAU, Heidelberg, EARL E. BRABB, ROBERT K. MARK,
and RICHARD J. PIKE, Menlo Park

with 5 figures and 5 tables

Summary. Morphometric types and map units were computed for the entire state of New Mexico fro eight-million-point digital elevation model (DEM). An automated version of the landform-classific procedure, developed for contour maps over 30 years ago by E. H. HAMMOND, sequentially evaluates the three descriptive measures: slope, relief and profile type. The DEM, at a spatial resolution of 200 m, was de from the same 1:250000-scale topographic maps used by HAMMOND. Although size of the 9.8 × 9.8 km m smaple-space also is close to HAMMOND's (9.65 × 9.65 km), the frequency of its placement by the compu 2500× greater. Our initial experiment in converting HAMMOND's semi-quantitative system to a computerize fully numerical procedure yields map patterns resembling HAMMOND's over much of New Mexico. Th outcomes show adequate correspondence in broad-scale meso and macro structures, although the morphor sub-classes themselves are not the same. Detail differences between the two results – which reflect contra map generalization, coarseness of the sample design, and other effects – remain to be explained.

Zusammenfassung. Auf Basis eines digitalen Höhenmodells mit 8 Millionen Gitterpunkten wurden fi gesamten US-Bundesstaat New Mexico geomorphometrische Typen von Reliefeinheiten berechnet. automatisierte Version des von E. H. HAMMOND vor über 30 Jahren für Höhenlinienkarten entwickelten V rens einer Reliefformklassifikation berechnet folgerichtig die gleichen drei deskriptiven Maßeinheit Neigung, der Höhendifferenz und des Profiltyps. Das digitale Höhenmodell wurde mit einer Auflösun 200 m vom gleichen topographischen Kartentyp des Maßstabs 1:250000 abgeleitet, der bereits von HAM verwendet wurde. Obwohl die Größe des gleitenden Analyseraumes (gleitendes Fenster) mit 9,8 × ebenfalls der von HAMMOND verwendeten Größe (9,65 × 9,65 km) nahe kommt, wurde die Häufigk räumlichen Versetzung des gleitenden Fensters bei der automatisierten Vorgehensweise 2500mal größer ge Unser ursprüngliches Experiment der Konvertierung von HAMMONDs halbquantitativem System in ein con gestütztes, ausschließlich numerisches Verfahren liefert kartographische Muster, die HAMMONDs Reliefei für die meisten Gebiete New Mexicos ähneln. Beide Resultate zeigen adäquate Übereinstimmungen großdimensionalen Meso- und Makrostrukturen, obwohl die geomorphometrischen Untereinheiten selb denen von HAMMOND entsprechen. Detailunterschiede zwischen den beiden Ergebnissen, die Unterschi Kartengeneralisierung, der räumlichen Auflösung bei der Datengewinnung und andere Einflüsse widers verbleiben weiterhin erklärungsbedürftig.

1 *Introduction*

This paper describes the automation of a manual approach to the numerical modelling of variability in topography. The rationale dates back to ALEXANDER VON HUMBOLDT, who *geomorphometry* (or simply morphometry) as the characterization of landforms by qua descriptions of the shape of Earth surface forms and by quantitative measurements of the "p constitution" of the Earth surface (VON HUMBOLDT 1849). The morphometric model present is implemented by Geographic Information Systems (GIS) technology and uses a digital el model (DEM) as raw data. Our example, the entire state of New Mexico, United States, is in its spatial scale.

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