Putting AI to Work in Geoscience

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Scientists in research and industrial facilities are now becoming increasingly involved in the study of artificial intelligence (AI), in which computer systems are being designed to emulate human behaviour. This article reviews the recent use of AI techniques in such diverse geoscience problems as the modelling of geological processes, the prediction of mineral and petroleum deposits, reasoning in more than one dimension, and the interpretation of typical data from geophysical surveys. Some 37 expert systems used in geology are analyzed and described. (Ed.)

Introduction

Artificial intelligence, or AI, is a field of computer science that strives to design machines to imitate human behaviour and intelligence. AI computer programs differ from traditional ones in their ability to manipulate data and logical inferences as well as to solve problems in a symbolic manner, as opposed to an algorithmic and purely quantitative manner. AI programs commonly accept data that may be incomplete, ambiguous or uncertain. Scientists have been involved in AI research for over 30 years, but it is only in the past decade or so that these computing methods have been applied to actual problems and that commercial AI products have become available.

AI encompasses four broad and often overlapping areas: natural language understanding, machine learning, computer (or machine) vision, and expert systems (Waterman, 1986). Certainly the most rapidly expanding, well-publicized and controversial of these is the field of expert systems - the design and implementation of computer programs that set out to rival the problem-solving ability of human experts in specific fields (Fig. 1). The application of these new techniques to geoscience is described here, the man-machine interface and computational aspects of AI being described elsewhere (Yatabe and Fabbri, 1988).

Figure 1: A micro VAX-based workstation used at the Canada Centre for Remote Sensing to develop expert systems for image processing. See Goodenough et al., 1987.

AI research has recently been experiencing financial and technical difficulties, possibly due to unrealistic expectations of what can be achieved. Much of the available literature is of a general and preliminary nature, but the geological requirements for automated reasoning are beginning to surface. Despite the problems in applying AI to geology, such as the difficulty in translating the geological knowledge into a computational form, positive trends can be recognized. Many disciplines of the geosciences are becoming involved in AI research, with a focus on representing imprecise and uncertain information, and on exploiting the spatial nature of geological data. The work is obviously aided by the ever increasing capability and availability of computers and the decreasing cost of personal computers.

AI and Expert Systems

In order to construct an expert system, the knowledge of the human expert must be transformed into computer code. This is usually done by a specialist called a "knowledge engineer." Acquiring the knowledge is a difficult, iterative process usually done through a series of interviews between experts and a knowledge engineer. Even though researchers are now seeking ways to acquire this knowledge in an automatic fashion, knowledge engineering is still a vital element in the process. The finished expert system carries out tasks involving, for example, reasoning, sequencing of tasks and explanations, and it can be used by a non-expert, who may request specific information on the current problem.

The structure of an expert system is organized in two separate parts, the knowledge base and the "inference engine." The former contains both facts and rules, whereas the latter controls the reasoning and sequencing mechanisms of the system and is typically generic to the task. It is subdivided into an interpreter, which makes logical inferences (applies the facts and/or rules) and a scheduler to sequence them. The interface between the expert system and the user can be a natural language, such as English, a graphic interactive tool, or other types of person-machine interaction.

There are several ways in which knowledge can be represented in order to solve a problem. The simplest of these is based on rules of the form exemplified by Table 1. These consist of an IF part (premise or condition) and a THEN part (a conclusion or action). Table 1 shows "production rules" of increasing complexity from I to V. In rule I, the premise consists of three parts, linked by "AND" relationships. In II, the conclusion consists of a list of values. Rule III has three parts in its premise, and the conclusion consists of four actions. In rule IV, the conclusion has a weight to 1.0 for the presence of suggestive evidence. Some rules provide numerical values of probability or confidence. An example is number V where one weight (20) is associated with the presence and another (1) with the absence of evidence, and an *a priori* probability associated with the hypothesis confirmed by the conclusion.

When related rules are linked together to make an inference, they form "inference networks," as in PROSPECTOR, one of the earliest expert systems developed (Duda et al., 1978, 1979 and Duda, 1980). These rules can be based on heuristics, or rules of thumb, which are short cuts that

TABLE 1: Examples of rules from expert systems designed for geological applications.

(I) Log analysis interpretation

"IF the water fit is normal and the Rw quality is excellent and there are more than 10 ft of hydrocarbons THEN the hydrocarbon presence is significant" (Apté and Weiss, 1985, p. 586, ELAS).

(II) Volcanological prediction

"IF the preceding eruption dates from between 100 and 1000 years ago, THEN the probabilities that the VEI (volcanic eruptivity index) are 0, 1, 2, 3, 4, 5 or 6 are 11, 5, 45, 26, 6, 4 and 1%, respectively" (Rosenthal-Sabroux et al., 1984, p. 107).

(III) Dipmeter test interpretation

"IF there is a delta-dominated, continental-shelf marine zone, and there is a sand zone intersecting the marine zone, and there is a blue pattern within the intersection, THEN assert a tributary fan zone: top = top of blue pattern; bottom = bottom of blue pattern; flow = azimuth of blue pattern" (Smith, 1984, p. 63; Dipmeter Advisor).

(IV) Seismic event identification

"IF (1) the focal depth of the event is deeper than 30 km, and (2) the location of the event is within a populated area, THEN there is suggestive evidence (1.0) that the seismic event is an earthquake" (Liu, 1985, p. 461).

(V) Mineral exploration

"IF intrusive breccia, RCIB, is present THEN (20,1) suggestive morphology if igneous rocks, SMIR (0.03)," where RCIB is the evidence, SMIR is the hypothesis, (20 and 1) are the values of likelihood sufficiency (LS) and necessity (LN), respectively, associated with presence and absence of the evidence, and (0.03) is the prior probability associated with the hypothesis SMIR (Gaschnig, 1982, p. 51, Fig. 3.1).

reduce the processing steps required for a solution. In contrast, an algorithmic rule would be rigidly applied and many iterations carried out before a solution is reached. Another method of representing knowledge is based on "frames," in which features are associated with nodes representing concepts or objects that can be organized into a hierarchy (Waterman, 1986). Each node has associated attributes and values that can be automatically inherited elsewhere in the hierarchy. Semantic and taxonomic networks, which store an organized set of names representing objects or relations, may also be used to simplify the description of facts. In practice, an inference network is a special instance of a semantic network.

The inference engine may reason in several ways, according to the data supplied to it. It can proceed from one rule to the next, continually updating its understanding, until it is able to make a decision. In one case, it may be given some facts, then search for a combination of them in agreement with *a priori* specifications in order to establish a hypothesis. This is called "forward chaining" or "data-driven

search." In the other case, a hypothesis or model is first defined, then the supporting rules, and finally the supporting facts are arrived at. This is called "backward chaining" or "goal-driven search." Most expert systems covered in this survey were either backward chaining or forward chaining. Only a few have the capabilities to handle both types of inferencing.

An important ability of many expert systems is that of accepting evidence that has some degree of uncertainty attached to it. This involves the use of probability measures, certainty factors or likelihood measures, such as those shown in rule V of Table 1. This example is taken from PROSPECTOR, where geological reasoning was extensively developed. In this situation, two likelihood measures, LS and LN, are used. They can be modified during interaction with a user, depending on the certainty of the evidence that the user provides. Certainty is provided as an interger between -5 and +5, respectively denoting absolute certainty of absence and of presence of the evidence. The two likelihood measures are modified by this interaction before the rule is activated towards the hypothesis connected to it in the inference network. This modifies the *a priori* probability for the hypothesis.

For example, as described by Duda and others (1979) for PROSPECTOR, and shown in Figure 1, the definite presence of the evidence RCIB multiplies the "odds" of SMIR by a factor 20, raising its probability from 0.03 to 0.382. Here RCIB is the abbreviation for evidence of the presence of intrusive breccias, and SMIR is the abbreviation for the hypothesis suggestive morphology of igneous rocks. The prior odds on SMIR are $0.03/(1-0.03)=0.030927$, giving posterior odds on SMIR equal to $20*0.030927=0.61855$ ($1*0.030927=0.030927$ for the observed absence), which corresponds to a probability of $0.61855/(1+0.61855)=0.382$ ($0.030927/(1+0.030927)=0.030$ for the observed absence). Here odds and probability are freely interchangeable through the simple relation $O=P/(1-P)$, where O =odds, and P =probability. Hence, $P=O/(1+O)$.

Bayes' rule can be stated as $O(H|E)=LS*O(H)$, where E indicates the evidence, H the hypothesis, and LS is the likelihood sufficiency. Often a level of confidence can be associated with the volunteered piece of evidence E' . The level of confidence modifies the *a priori* probability of the hypothesis H , as well as the other hypotheses in the network, until the goal state is reached. In our example, the goal state is "a porphyry copper deposit is (or is not) present."

A Survey of Expert Systems in Geoscience

The majority of the papers published in the 1980s covering AI applications within the geosciences have been descriptions of expert systems in various stages of completion. An extensive literature search carried out on this topic is represented in Table 2. This describes the geological discipline or subfield covered, and the function and purpose of the expert system.

Table 3 gives further characteristics of each of the 37 expert systems. How is knowledge represented? - production rules, semantic networks or frames? What kind of inference is used in the system - is it a forward or backward chaining system, or a modification of these, and can imprecision and uncertainty in the data be represented? Does the system involve some form of spatial reasoning so that it provides information on the extent of some object or positional property in two or more dimensions? Is there some communication to an external database or conventional software package that lies outside the expert system itself? What computer language or shell was used for programming? On which machine does this expert system operate? What was the status of the project at the time that the paper was written or when the system designer was contacted? Was AI necessary for solving the problem most effectively?

TABLE 2: Expert systems for geoscience applications: discipline and function

EXPERT SYSTEM	REFERENCE	GEOLOGICAL DISCIPLINE	FUNCTION
1 The Deciding Factor	Campbell and Fitzgerald 1985	Decision Making	Expert Shell
2 Mud	Kahn and McDermott, 1984	Drilling	Diagnosis and Debugging
3 Drilling Advisor	Waterman, 1986	Drilling	Diagnosis and Debugging
4 ---	Gero, 1985	Engineering geology	Identification Planning
5 CESSOL	Laurent and Mouglin, 1984	Engineering geology	Planning
6 GPEN	Smith et al., 1986	Geophysical drilling, mineral exploration	Interpretation
7 BOU-1	Dimitrakopoulos, 1987	Geostatistics	Advisor
8 Gridding Advisor	Maslyn, 1987	Gridding of geological map data	Advisor
9 EXPAR	McClymont and Schwartz 1985	Hydrogeology	Interpretation, Planning
10 INTAL	Hawkes, 1985	Igneous petrology	Identification
11 LITHO	Bonnet et al., 1983	Log analysis for oil exploration	Interpretation
12 KBS	West, 1985	Mineralogy	Identification
13 PROSPECTOR II	McCammon, 1987	Mineral Exploration	Identification
14 GEOEVALUATOR	Koch and Papacharalampos 1988	Mineral exploration	Prediction
15 muPROSPECTOR	McCammon, 1984	Mineral exploration	Identification
16 FINDER	Singer, 1985	Mineral exploration	Prediction, Simulation
17 PROSPECTOR	Duda et al., 1978	Mineral exploration	Identification, Prediction
18 ---	Ennis, 1986	Natural Language Processing system for cartography	Parser
19 ELFIN	Martin-Clouaire, 1984	Oil exploration	Interpretation, Prediction
20 SRPS	Fowler, 1987	Oil exploration	Prediction
21 Dipmeter Advisor	Smith et al., 1985	Oil exploration	Interpretation
22 OILXPRT	Fang et al., 1986	Oil exploration	Interpretation
23 EXPLOR	Maslyn, 1986	Oil exploration	Prediction
24 ELAS	Apté et al., 1985	Oil exploration	Advisor
25 EXPAL	Conrad and Beightol, 1988	Paleontology and database management	Identification
26 FOSSIL	Alexander, 1985	Paleontology	Identification
27 LES	Perkins, et al., 1985	Photointerpretation	Interpretation
28 GEOX	Chiou, 1985	Remote sensing	Identification
29 ---	Erickson and Likens, 1984	Remote sensing	Image Interpretation
30 GEMS	Papacharalampos, 1988	Remote sensing	Interpretation
31 EMACS	Janakiraman, 1986	Reserve estimation	Prediction
32 ---	Krystinik, 1985, 1986	Sedimentology	Identification
33 muPETROL	Miller, 1986, 1987a, b	Sedimentology	Identification
34 RESOLVER	Love and Simaan, 1985	Seismic interpretation	Image Interpretation
35 ---	Liu, 1985	Seismology	Identification
36 GOLD	Lister et al., 1987	Spectroradiometry	Identification
37 ---	Rosenthal-Sabroux et al., 1984	Volcanology	Prediction, Planning

The geoscience disciplines covered include such diverse areas as mineralogy, paleontology, remote sensing, volcanology, engineering geology and geostatistics but most (17) deal with petroleum geology and mineral exploration. Most applications can be grouped into identification, interpretation, advising, prediction, planning, or diagnosis/debugging. The systems performing identification and interpretation tasks accept as inputs physical observations from hand specimens, field surveys and laboratory tests. The advising systems guide the user through the manipulation of a conventional software package. Prediction systems attempt to locate and estimate the extent of oil and mineral deposits. Planning systems design programs for preventive or exploratory measurements. The diagnosis-debugging systems are all related to trouble-shooting of drilling technology problems.

By far, the largest number of expert systems surveyed are based on explicit production rules, and nine are capable of spatial reasoning. Twenty-two of the expert systems were based on a symbolic programming language such as some variant of LISP or PROLOG, or based on expert shells such as EMYCIN, OPS5 or KS3000. Apparently, a symbolic programming language is not a prerequisite for an operational expert system.

Expert systems developed in the early part of this decade were based on relatively large minicomputer systems such as the VAX. Nine of the surveyed systems were based on

mainframe computers, and only five were built on symbolic workstations. Many of those developed in the past two or three years have been based on small, inexpensive micro-computers; 16 were PC-based.

Systems that appeared to be proposals rather than working systems were labelled as such in the "Status of Project" section of Table 3. If an expert system successfully accomplished the tasks it was designed to achieve, it was labelled as "completed" in the table, although it was not clear to what extent this was true. Systems beyond the proposal stage, which did not yet accomplish their intended tasks, were labelled as "partially completed." Only 15 systems could be labelled "completed," according to these criteria.

Tables 2 and 3 show that not all expert systems can accept imprecise or uncertain data. Spatially distributed information, including remotely sensed and other map data, is being examined at various levels of sophistication. In many cases, AI components constitute only part of a computer program, acting as intelligent interfaces to more conventional algorithms or databases. In 23 expert systems out of the original 37, the usage of AI was confirmed as being necessary. Table 4 summarizes the most important characteristics of some representative expert systems.

PROSPECTOR

Probably the best-known expert system in geology is PROSPECTOR, a program to assist in mineral exploration (Duda, 1980). In this system the reasoning process of an experienced geologist is emulated to evaluate the

likelihood that a mineral prospect or region resembles one or more models built into the knowledge base. Several ore deposit models have been encoded, which reached different degrees of development in terms of their semantic networks, descriptive text and testing.

Inference, semantic and taxonomic networks were used in PROSPECTOR, the inference network that was described earlier. As shown in Figure 2, logical, plausible and context relations were distinguished in the reasoning processes represented in the networks (Gaschnig, 1982). To facilitate the building of the models and of the different networks, a knowledge acquisition system (KAS) containing an editor (RENE) was programmed by Reboh (1981) as an empty shell for general purpose knowledge engineering.

A user provides information about a prospective geological site including the type of terrain, mineralogy, geographical location or structure. The program compares these inputs with the built-in models in its database. After prompting the user for more information, it makes a report on the type of mineral deposit that it assesses to be present, plus a degree of confidence associated with this conclusion. West (1985) cautions, however, that there are two major disadvantages to numerical methods for establishing measures of confidence such as that of PROSPECTOR. First, experts in the particular field may find it difficult to provide figures for measures such as the prior probability, LS and LN, because the applications themselves are imprecise. Second,

In the interactive mode, PROSPECTOR provides on-line consultation. Two other kinds of operation have been programmed: a batch mode to process data from questionnaires and for model-performance testing, and a graphic input/output mode whereby maps are placed on a graphic tablet digitizer to obtain digital contour maps. Such maps provide spatially distributed evidence for "drilling-site-selection" models for which field and map evidence are combined (Duda et al., 1978, Duda, 1980). An image processing system produces and shares digital image files, of up to 128 x 128 pixels or cells, with PROSPECTOR. These files, evaluated by the inference network, produce a simplified digital map of a prospective area. Elementary spatial reasoning is built into the drilling-site-selection models by rating cells according to their linear distance from contours or traces of fractures (Duda et al., 1978). Unfortunately, no action followed the experiments on drilling-site-selection models of 1979.

PROSPECTOR II, currently under development (McCammon, 1987), differs from PROSPECTOR in two significant ways. First, it uses frames to represent "rules," which simplify model building and permit the easy management of a large number of models. One example is shown in the "bitmap window" in the upper right portion of Figure 3 (see inset A). The second difference between the two systems is that the volunteer mode of

Figure 2: Part of inference network for a hypabyssal (HYPE) porphyry copper deposit model in PROSPECTOR. After Reboh, 1981, p. 13, Fig. 3. Logical (AND-OR), plausible (solid arrows) and contextual (dashed arrows) relationships or rules are represented. Inside the boxes are the statements of evidence or hypotheses; above to the left are the abbreviations, and to the right, the values of a priori probabilities. The values of likelihood sufficiency and necessity appear along the solid arrows; the context interval appears below the dashed arrows.

		Knowledge Representation				Inference Mechanism		Imprecision and Uncertainty		Spatial Reasoning		Communication		Host Computer		Status of System	
																	Was, At Necessary?
EXPERT SYSTEM																	
1	DECIDING FACTOR	R	FC	YES							PAS	PC	CM	N/A			
2	Mud	R	FC	YES							OPS5	MA	CM	YES			
3	DRILLING ADVISOR	R	BC	?							KS3+S1	SW	CM	YES			
4	---	R	?								PR	PC	CM				
5	CESSOL	R	BC FC								?	PC	PCM	?			
6	GPEX	R F	FC	?							LSP	SW	PCM	YES			
7	BOU-1	R	FC								LSP	PC	PCM	YES			
8	GRIDDING ADVISOR	R	BC								mPR	PC	CM				
9	EXPAR	R	?	YES				YES			?	PC	PCM	YES			
10	INTAL	R	KS								BAS	PC	CM				
11	LITHO	R	BC	YES				?			EMY	MI	CM	YES			
12	KBS	R	BC								?	?	?	?			
13	PROSPECTOR II	F I S	BC FC	YES							ILSPD	SW	PCM	YES			
14	GEOEVALUATOR	R	BC	?	YES						muLSP	PC	PCM	?			
15	muPROSPECTOR	R I	BC					YES			muLSP	PC	CM	YES			
16	FINDER	?	?		YES			YES			PAS	MA	CM	?			
17	PROSPECTOR	R I S	BC FC	YES	YES						ILSP	MA	CM	YES			
18	---	N/A	?					YES			LSP	MA	PCM	?			
19	ELFIN	R	FC	YES	YES						LSP	MA	PR ?	YES			
20	SRPS	R	FC?								BAS	PC	CM	YES			
21	DIPMETER ADVISOR	R	FC								ILSPD	SW	CM	YES			
22	OLXPERT	R	FC ?	YES	YES						LSP	PC	PR	?			
23	EXPLOR	R	FC		YES			YES			BAS	PC	CM	?			
24	ELAS	R	?								EXP	MA	CM	YES			
25	EXPAL	R	?					YES			?	PC	PCM				
26	FOSSIL	F	?								mPR	PC	?	YES			
27	LES	R	BC ?								?	?	PCM	YES			
28	GEOX	F	BC		YES						LSP	MA	PCM	YES			
29	---	R	?		YES						LSP	SW	PCM	YES			
30	GEMS	R	FC BC								PAS+LSP	PC	PCM	?			
31	EMACS	R	BC	YES				YES			LSP	?	PCM	YES			
32	---	R I	BC	YES							ILSP	MA	CM	YES			
33	muPETROL	R I	BC								muLSP						

operation in PROSPECTOR II has been expanded to exploit the graphics display capability of the Interlisp-D programming environment. A user can select items that relate to descriptions such as rock type, geologic age, minerals and geochemical elements. Input is interpreted in the same manner as in PROSPECTOR and results are shown in the window in the left centre portion of Figure 3 (inset B). A diagram of a particular model, also shown in Figure 3, is easily retrieved. The next logical stage of development of PROSPECTOR II is to incorporate spatial data to be interpreted by the system.

Those systems based on PROSPECTOR or variants of it have retained the original inference network. However, only PROSPECTOR II has retained its semantic network. The remaining PROSPECTOR-based systems (The Deciding Factor, muPROSPECTOR and muPETROL) were rewritten for microcomputers. The Deciding Factor contains a sim-

TABLE 4: Representative Examples of Expert Systems in Geology

Main Characteristics	Name of System
Inference, semantic nets, imprecision, uncertainty (frames).	PROSPECTOR (PROSPECTOR II)
Expert shell for mainframe.	KAS
Expert system converted to microcomputer.	muPROSPECTOR
Expert shell for microcomputer (commercial product).	The Deciding Factor
Search program.	INTAL
Simulation of search patterns.	FINDER
Interface to a geostatistical package.	BOU-1
Graphic interaction and pattern recognition (commercial product).	DIPMETER
Spatial and temporal reasoning, usage of metarules, imprecision, uncertainty.	ADVISOR
	ELFIN

plified version of handling uncertainty, derived from PROSPECTOR. It also provides a "friendly" editor for building inference networks with a dendrogram-like structure.

muPROSPECTOR was developed for a microcomputer using the language muLISP (McCammon, 1983, 1984 and 1986). It was adapted so that others could tailor it to a variety of problems such as mineral endowment estimation (Koch and Papacharalampos, 1988) sedimentary basin analysis (Miller, 1986, 1987a, b), and regional geological environments at the district and outcrop level (McCammon et al., 1984, McCammon, 1985). muPROSPECTOR enables rules with ternary choices (YES, NO, DON'T KNOW) or multiple choices for which menus are generated. Explanations and facilities for summarizing conclusions are available, which make it relatively easy to store knowledge about events or geological objects. In its simple structure, no provision is made for complex reasoning with uncertainty weighting.

INTAL

An expert system has been designed by Hawkes (1985) to enable an inexperienced geologist, with a knowledge of common rock-forming minerals, to identify igneous rocks from hand specimens. This process is based on a physical description in English, and the INTAL system is programmed

in BASIC and operates on a microcomputer. Best described as a keyword search program, INTAL interactively scans the input for certain keywords relevant to rock identification (such as those relating to crystallinity, grain size and texture) rather than performing as a parsing system. The program has generated some interesting discussions on nomenclature among professional geologists, and it promises to be a useful teaching tool.

FINDER

The integration of spatial patterns for geochemical samples in mineralized and barren areas was used

Figure 3: The user interface of PROSPECTOR II. The Inter-lisp-D environment allows one to use overlapping windows. Bitmap at the top right is a listing of the Sn-greisen model. Below it is a model diagram. A large bitmap on the left is the resulting evaluation. R.B. McCammon, personal communication.

by Singer (1985) in designing FINDER, an artificial intelligence program written in PASCAL for a mainframe computer. Target areas are selected by means of geological, geochemical and geophysical variables sampled regularly over a region. The rule-based program uses Bayesian statistics and a powerful area-of-influence method of variously shaped targets with preferred orientation. FINDER provides estimates of the number of deposits for each target shape, size and anisotropy. Results are in the form of contour maps, character plots and tables. A simple interaction with prompts and explanations is used by the program. Singer (1985) commented that although strictly speaking FINDER is not an expert system it employs the principles of AI to simulate spatial patterns given target geometry and the position of samples or drill holes.

DIPMETER ADVISOR

Of the few commercial expert systems available in geology, perhaps the most complete is the DIPMETER ADVISOR system for well-log interpretation developed at Schlumberger (Smith, 1984). Oil-well logs record measurements made by geophysical tools first lowered into boreholes, then raised out of them. Sequences of values for rock conductivity in different directions, gamma-ray values, resistivity and so forth can soon be integrated with measurements of the inclination and orientation of the tool to estimate the magnitude and azimuth of the dip or tilt of various formation layers penetrated by the boreholes.

This information is combined with knowledge of local geology and measurements from other logs, such as lithology, dip pattern or depositional sequences. Characteristic dip patterns and their connectivity are identified by a pattern recognition procedure through a sophisticated graphic interaction, as shown in Figure 4. A large amount of effort went into developing the user interface, to which 42% of the programming code is devoted. An example of a rule for this expert system is shown in Table 1.

Some Other Examples

A promising use of AI technology has been to provide intelligent interfaces to statistical packages (Gale, 1986). BOU-1 (Dimitrakopoulos, 1987 and Dimitrakopoulos et al.,

1986) is an intelligent interface to VARIO3, a program for variogram calculation and evaluation of experimental characteristics (Geostat Systems International Inc., 1983). Interaction with the user facilitates the collection of the required data and its transformation into processable form, calls conventional subroutines for calculation of specific values, and outputs results and their interpretation.

Spatial and temporal reasoning, control of reasoning through rules and metarules (rules governing other rules) and approximate reasoning are used in ELFIN (Martin-Clouaire, 1984). This expert system was designed to assist a geologist in the study of hydrocarbon migration from a source rock into a reservoir zone. It is based on principles of possibility theory developed by Zadeh (1978) to take imprecise knowledge into account (Martin-Clouaire and Prade, 1984).

Computer Vision

Though most computer vision research has been restricted to fields that lie outside of geology, research in this area is worthy of brief mention, because geology is likely to benefit greatly from this field. Computer vision techniques have been used for automatic photo-interpretation and map interpretation systems. AI has been used to represent symbolically visual knowledge and interpret man-made objects from aerial photographs (Shapiro, 1985, Nagao and Matsu-

Typical Geologic Interpretation Problem and Solution

1. Deposit Sandstone
2. Deposit Shale
3. Uplift
4. Intrude Mafic-Igneous
5. Tilt
6. Fault Across Shale and Sandstone, Across Shale and Sandstone, (with a slip of 76 meters).
7. Erode Shale and Mafic-Igneous

Solution to figure at left with Parameter Values

1. Deposit Sandstone (to a depth of 450 meters below sea level).
2. Deposit Shale (to a depth of 30 meters below sea level).
3. Uplift (by 200 meters).
4. Intrude (80 meters of) Mafic-Igneous (at an angle of 78 deg.).
5. Tilt (by -16 deg.).
6. Fault (at an angle of 108 deg.) Across Shale and Sandstone, (with a slip of 76 meters).
7. Erode Shale and Mafic-Igneous (to sea-level).

Figure 4: Stratigraphic analysis interaction in the DIPMETER ADVISOR. After Smith, 1984, Fig. 3, p. 4.

yama, 1980, Matsuyama and Hwang, 1983, and McKeown, 1984). Fabbri and others (1988) have reviewed applications of AI to remote sensing, describing in particular the use of AI techniques in land cover analysis, clear-cut monitoring and image classification. Cartographic and geographic knowledge are also being modelled; Mackworth (1977) and Havens and Mackworth (1983) have developed a program to interpret maps sketched either freehand or on a graphic tablet.

The analysis, interpretation and manipulation of spatially distributed data in geology is still affected by the complexity of spatial relationships both in cross sections and in maps or digital images. A technique proposed by Simmons (1982, 1983) termed "imagining," attempts to simulate geological events by reasoning from geological cross sections (see also Simmons and Davis, 1983). Figure 5 shows, on the left, a cross section and a plausible sequence of events to explain the relationships illustrated.

To simulate geometrically a sequence of events, it is necessary to insert reasonable and realistic parameter values in the symbolic sequence (shown in middle illustration). More-

Figure 5: "Imagining" in the simulation of geological cross sections. After Simmons, 1983, Figs. 1 to 4. For explanation see text.

over, such parameters have to be translated into usable measurements from the same section for which a sequence of events has to be simulated (illustration on right). Both quantitative and qualitative simulations are required to approximate the known cross section; neither simulation alone seems to suffice. Comparisons between a simulated section and the goal (original section) are made to assess the results.

Many geological interpretations and models are based on visual representations such as maps, cross sections, aerial photographs, satellite images, rose diagrams, contour maps and other forms of diagrammatic information, in which spatial characterization is fundamental. Computer vision can provide new tools for automatic spatial reasoning in geology.

The Current Status of AI in the Geosciences

Research on AI, and particularly expert systems, ran into major problems in 1986 and 1987. Companies attempting to exploit AI techniques, as well as academic institutions working on pure research, have experienced many technical and financial difficulties (Lamb, 1986). The literature covered in this review provides some clues as to why this is so.

Many of these difficulties may be seen as the normal result of unrealistic, even misleading, expectations of what AI has accomplished and what it could achieve in many domains. In some cases, the vendors of expert-system tools are guilty of overrating the power of their products and underestimating the effort required to build a system that will solve real problems (Bobrow et al., 1986). Some of the claims made by AI promoters have fuelled much excitement.

For instance, it is said that high order languages such as LISP and PROLOG make it possible to create, debug and maintain very complex programs. These are especially suited for modelling human intelligence and expertise

because they use symbolic inference and forms of knowledge representation, such as production rules. Martins (1984) stated that, in practice, software development is expensive, takes a very long time and is computationally heavy; the code is generally complex to understand, update and maintain.

It appears that many authors of expert-system proposals do not have a clear idea of what they wish their system to accomplish. A major limitation is the lack of attention given to the user, including level of experience and expectations. Moreover, a disparity often exists between an expert's knowledge formulation and how it is entered into the computer: proper procedures and tools are still needed to translate knowledge into computational form. In most of the expert systems studied here, the knowledge representation is limited to one form, generally rules, a single representation that may not be adequate for complex tasks. Of course, many of the problems observed in the development of expert systems are similar to those encountered in any software development project, such as unclear goals and specifications and lack of proper representation and/or user interface.

What we see as very promising trends in the geosciences for the usage of AI include the use of spatial reasoning, new capabilities to simplify the understanding of complex problems, and procedures and tools to allow a user to organize reasoning. Practically all subdisciplines of geology are involved, and there is the obviously increasing use of microcomputers, both in terms of software and hardware. The availability of advanced AI tools, such as shells and multiple display devices, is also encouraging, as are indications that scientists are more concerned with solving problems than using complicated tools or languages.

The expert systems considered here seem necessary in situations requiring many rules or reasoning steps, particularly if different lines of evidence must be combined to support a hypothesis. Quantitative spatial reasoning, something that is unnatural for humans, is required in the geosciences. Mathematical geology has already contributed

much towards the analysis of spatially distributed data through statistical methods such as trend-surface analysis and measures of spatial autocorrelation. These methods should now be extended to the construction of expert systems. What has been accomplished so far in the application of AI in the geosciences is perhaps little in terms of practical results, but the trend is clear. Some reasoning mechanisms can indeed become useful processing tools and perform successfully in well-understood situations of narrow scope.

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