A PROPOSAL OF ADAPTATION OF A KNOWLEDGE-BASED SCENE ANALYSIS MODEL TO SOME REMOTE SENSING PROBLEMS

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ABSTRACT

A scene analysis computer program, developed according to an AI paradigm, is described through its representational and control components. The available declarative knowledge about a domain or process can be stored in a particular type of associative network, in the form of concepts, part and particularization hierarchies, predicate calculus-like formulae or decision rules. Procedural knowledge can also be provided by many forms, as codes associated to attributes and predicates, actions to be performed after concept activation and control affecting heuristics. Control can be viewed as a series of propagation of alterations, problem solving and image measurements steps. The necessary adaptations to be performed over this program in order to store knowledge from experts on remote sensing and image analysis problems are discussed. Some of these problems are related to the analysis of geological sites, map guided interpretation and knowledge-based segmentation.

1. INTRODUCTION

Many research efforts in Artificial Intelligence (AI) have recently been directed to applicative areas where the knowledge about the domain or the processes has an important role on the effectiveness of the solutions of the problems under consideration. Knowledge representation models, such as semantic or associative networks, decision or production rules, frames and knowledge sources, were developed for both the declarative and procedural types of knowledge.

Expert systems were built around these models in order to capture the specialized knowledge of experts in a specific domain and also the way they make inferences or guesses from incomplete or imprecisely stated facts, by means of so-called "heuristics". Barr and Feigenbaum (1981, 1982) give an introductory description of these subjects; see also Hayes-Roth (1984) and Nau (1983). Some of the areas for which these techniques were already applied are: medicine (diagnosis assistants), geology, chemistry (for molecular structure elucidation), and continuous-spech analysis and image analysis, among others.

The scene analysis system will be commented firstly, along with its representation model and control module features. The objective of this work is to set under which conditions this system can be adapted to both already developed applications and to the potential ones in order to solve some problems related to remote sensing and image analysis. The proposed adaptations imply a number of modifications in the control module and in the explanation facilities, as well as some new features that must be added.

2. KNOWLEDGE REPRESENTATION AND THE SCENE ANALYSIS MODEL

Associative (or semantic) networks were first proposed for the internal storing of the meaning of words (Quillian, 1968), where nodes labelled with words were linked together by associative links. The first model was modified and improved, in many ways, in order to have explicit structures for particularization hierarchies, part hierarchies, propositional formulae which relate concepts and predicates, handling of time and intervals, modal operators, and the like. An important feature is the property inheritance: it is supposed that a particularization of a concept will inherit the properties of that concept (See Findler (1979) for a description of some of the known models.).

Scene analysis and the related problems of proposing perception models were also the subject of other studies. Psychological models are constrained to describing the results of the processes; many important aspects, such as the contradictory part-whole or whole-part analysis are not well-understood yet, although some insights were given by the application of quantitative time response analysis to restrited environments (Navon, 1977). Some perception cyle models were proposed to cope with the scene analysis problem; see, for instance, Hanson and Riseman (1978), Havens and Mackworth (1980) and Ohta (1980).

The implemented model at INPE exploits the declarative aspect of the knowledge representation which means that what is known and available about a domain is stored as independent chunks of knowledge (data). Procedural knowledge can also be stored, as will be commented soon. Another feature refers to the perception cycle: a previously programmed cycle is available, although alterations can be made on it through control commands, heuristics and hierarchy activation. The structure of the model will be briefly commented below and has been already described elsewhere (Simoni, 1986; Simoni and Renna e Souza, 1983).

Figure 1 shows the system data flow. Symbolic and image dedicated processing are separated, the later one being activated either in spontaneous fashion or by nodes in the formulae or rules of the network.

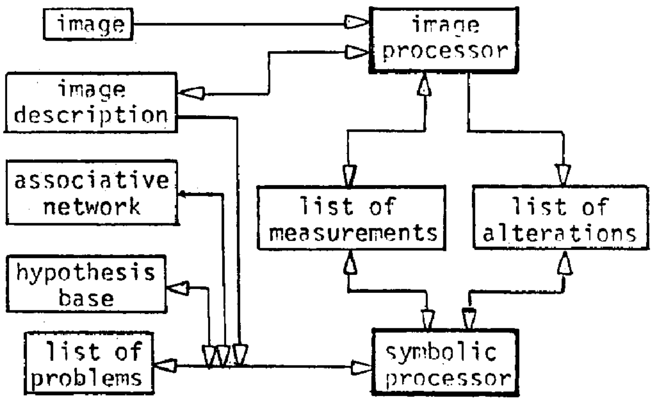

Fig. 1 - The system data flow.

The associative network which stores the a priori knowledge about a domain comprises, in short:

- A list of concepts, with pointers to part and particularization hierarchies, a list of reference to nodes of formulae or decision rules where each concept was used predicatively. There is also an associated code for actions to be performed after concept activation (for instance, to activate specific portions of the related hierarchies).
- A list of predicates, with pointers to a list of usage references, types (noncomputable, computable, geometric relation) and number for accessing truth-value associated code.
- A list of attributes, with pointers to a list of usage references, types (number, interval or list), associated code for computing their values and indication of automatic computation.
- A list of formulae and decision rules, expressed as quantified formulae where a first-order predicate calculus-like language is used for their acquisition.

The hypothesis base stores the instantiated part of the associative network, and it is composed of the instantiated concepts and their referents (pointers to a description, for instance), part relations, computed attributes or predicates and formulae or decision rules already employed.

The image is used as an input to the system; descriptions are generated from it (for instance, the obtained regions and their respective historic status, code associated to lines at the image, masks, etc. Skeletons are not represented at the current version of the system).

The list of alterations stores predicate and concept truth-values, as they are generated from the information processor and stores values coming from measurements done by the image processor. These alterations have an important role in the control mechanism; the hypothesis base is activated as a consequence of the inferences due to their propagation. The list of measurements stores awating requests of measurements on the image, being the requests generated by either one of the processors. The list of problems stores the concepts or predicates for which an instance is sought; problems may have subproblems associated to them.

As an example of the structures used in the representation, the following statements (1) and (3) give some facts associated with an arch, such as its structure and characterization. In formula (2), ADJACENT is an instance of a computable predicate which needs an executable code associated to it in order to compute its truth-value. The predicative usage of concepts (ARCH node) and their usage as part relations (LATERAL and LINTEL nodes, expressing the fact that the parts belong to the same arch) is also shown. The sintax of decision rules in this model is depicted in (3): premise and conclusion have a common set of quantifiers, the first one being an universal quantifier, and both of them may also have a specific set of quantifiers of limited scope. In this particular situation, the fact that the average colour of an region lies in some specific interval is a strong evidence for the region being interpreted as a lintel:

LATERAL PART-OF ARCH
LINTEL PART-OF ARCH (1)

$\forall x \forall y \forall z$ [[ARCH(x) AND LATERAL (x,y) AND LINTEL(x,z)] ---> ADJACENT(y,z)] (2)

$\forall x$ [COLOUR(x, interv) ---> (0.8) LINTEL (x)] (3)

In addition to the possibility of representing decision rules in the propositional part of the network, which greatly extends its representation power while keeping its uniformity, the use of computable predicates with their standard structure of arguments allows the insertion of executable code, as separately compiled procedures, for each specific application. Another extend capability of the model refers to the inference of part relations that allows some compression in the storage of the part hierarchies.

The scene analysis is performed by the two already mentioned kinds of processing, the symbolic and the image dedicated. The general structure of control is outlined at Figure 2. For the sake of simplicity, some feedback links were removed wherever they appeared internally to a list of actions.

If there exists an alteration to propagate or a problem to solve: - eliminate alterations already propagated, - determine actions to perform, - seek for suspended formulae or rules, - choose problem to solve, - choose alteration due to a tentatively altered value or to an unknown value, - access formulae or rules for inferencing.
Choose mapping: - eliminate alterations, - generate direction indications.
Employ mapped formula or rule for inference: - perform postinference analysis, - seek conditions for reinstantiating a formula or a rule.
Determine conditions for measurements on image: - choose next measurement, - set initialization actions.

Fig. 2 - The system control flow.

At the beginning of each cycle, a procedure for determining user specified actions is ran; in order words, it is possible to insert a heuristics there (for instance, for selecting a specific kind of problem to solve or alteration to propagate, to initialize a list, etc.).

During the inference process, a formula or rule being activated may be set as "suspended", either if a measurement on the image is necessary, and this is not allowed at that time, or if the activation implies the generation of problems to be solved before the activation is resumed. If the requested operation on the image was already done, or if the structure of associated problems was already traversed for solving them, some formula or rule may be ready to be reactivated.

If there is a problem to solve, a heuristics may also be invoked in order to choose the next one to be analyzed. If there is a nonpropagated alteration, the associated truth-value is checked and this may result in a question to be answered.

Any of these conditions (user chosen action, problem to solve, nonpropagated alteration) may set conditions for starting the inference process. A match algorithm is used in order to map the elements which triggered the process to the nodes of formulae or decision rules that may correspond to them. This is a complex algorithm: in which variables may have referents attached to them or may require a search process over the hypothesis base during the traversing process in order to verify the quantified expressions; in which fictitious elements may be added for nodes without correspondent in the hypothesis base and actual elements may be sought; in which a part relation inference process may occur, if there is one such kind of node in the formula or rule and in which subproblems may be generated if the algorithm was invoked to solve a problem, for instance.

Before starting the actual inference process, some indications are associated to formula or rule nodes, according to the existence of a question, computable predicates and other cases.

The inference process builds a list of provisional values for the concluded truth-values of instances of concepts, part relations and predicates. Whether the formula or rule was suspended or there were conflicts among old and newly concluded values, is analyzed after the completion of the traverse of nodes. The provisional values may then be inserted in the hypothesis base, with the corresponding hierarchy propagation. If the concluded values are such that some former inference does not hold anymore, a backtracking process is invoked.

If must also be noticed that decision rules can be used in a forward or backward manner.

If the image processor is in duty at a certain instant and there is no possible measurement to be performed, an initialization procedure may result in an user-chosen action or some other action, such as attaching a tentative interpretation to an uninterpreted entity.

The operations on the image include segmentation, histogram thresholding, shape and colour attributes, geometric relations and the like. There are some procedure "heads" available for computable predicates that can be used for inserting other operations.

3. PROPOSED ADAPTATIONS TO THE MODEL

The importance of AI (expert systems in particular) for remote sensing and related areas has already been emphasized by other authors. Mooneyhan (1983), for instance, when presenting the conclusions of a study conducted by NASA about an advanced remote sensing system, said that "the potential for application of expert systems to exploit improved remotely sensed data sources appears to be without limit". One of the most immediate uses of this technology would be, according to him, the detection and monitoring of natural and man-made changes in land surface cover and land use (see comments about the system of Goldberg et al. (1985) in this section, for instance, deforestation.The sketch of a knowledge-based digital image interpretation system for change detection applications was proposed by them; this system would comprise:

- an image interpreter, which receives input from corrected new image data and global data base, generates output to the change interpreter, and has rule bases for interpretation, classification and use;
- a change interpreter, which gets input from the image interpreter and global data base, generates output to the global data base, and has rule bases for radiometric change, classification change and use change;
- a cause interpreter, with causal models, and mensuration and update rules, being its input from the change interpreter and global data base, and being its output to the global data base;
- a global data base.

The area of geology it one that has been successfully treated by the techniques under discussion and still exhibits a wide spectrum of potential applications.

The analysis of geological sites, as demonstrated by the Prospector expert system, a consultant for mineral exploration (Duda et al, 1977; Gaschnig, 1980), is one of the applications of knowledge representation models to real world problems that has been tested and has shown practical results. This system intends to help geologists, first by accepting a set of imprecise statements about a particular prospect, comparing this information with models (stored as data) of ore deposits, and scoring the models; after this, the system starts an interactive session to get additional relevant information. The control for confirming the models is backward chaining, although volunteered information or changes in previous statements may be entered at any time. The knowledge representation uses "spaces" for storing the evidences (like "barita overlying sulfides"), which form the inference rules (like "IF widespread igneous rocks, THEN (LS, LN) vulcanic province"). The LS and LN degrees, which belong to [-5,5], measure the sufficiency of the antecedent to the consequent and the necessity of the antecedent for the consequent. There is also a taxonomic network for subset relations (like the relation between sulfide and mineral). The problems that must be addressed are those of representation, inference, control and explanation; future extensions include a limited form of natural language processing.

The Prospector's inference rules may be stored as decision rules with the aid of delineations of the relations used by it. For instance, (4) is the description, and (5) and (6) are the coding for the antecedent and consequent spaces of an inference rule; (7) is one of the possible corresponding decision rules, where concepts predicatively used (like SILICA and RHYOLITE) represent the assumed composition of a prospect. The Prospector's taxonomic network can not be fully reproduced by the particularization hierarchy due to sets with more than one superset (for instance, magnetite can be iron oxide or spinel); one can suppress the least common usage (adding the suppressed one in the spaces when needed) or generate artificial classification nodes.

```
"IF silica and sulfide-filled cracks in
    rhyolite or dacite or andeside
THEN (3.0) Kuroko-type massive sulfide
    deposit                                      (4)

((E-16A (COMP-OF-16A (AND SILICA SULFIDES)))
 (E-16B (COMP-OF-16B (OR ANDESITE DACITE
                         RHYOLITE))
     (ENTITY-PROP-16B CONTAINING-CRACKS))

 (PHYS-REL-16AB (CONTAINED-IN E-16A E-16B))
 (LOC PROSPECT))                                 (5)

((E-0 (MEMBER-0 MSD)
 (LOC PROSPECT))                                 (6)

∀x ∀y [ TARGET-AREA(x) E PROSPECT(x,y) E
     Eu Ev [ENTITY(y,u) E ENTITY(y,v) E
            [ SILICA(u) E SULFIDES(u)] E
            [ RHYOLITE(v) OU DACITE(v)
              OU ANDESITE(v) ] E
            CONTAINING-CRACKS(v) E
            CONTAINED-IN(v,u) ]]
   ---> (n) MSD(x) ]                             (7)
```

In order to cope with the subjective probabilities associated with evidences and to compute Prospector's effective likelihood ratios associated with rules, these computations must be performed through special procedures that are associated with value changes. It is also necessary to change the interpretation of rule degrees from numbers to pointers for a list.

The knowledge base must support both askable and unaskable evidences. Whenever a decision rule node that corresponds to an askable evidence is traversed, the user must be asked about the evidence and attribute-related predicates if the evidence is not available yet (interruptions must be generated during the traverse for analyzing quantified expresssions, in order to solve a problem or to propagate facts).

Volunteered information must be also accepted at any point of a session, either at its beginning or during the interruptions for the asked evidences. This new information may be labelled as nonpropagated and will induce a hierarchy activation and a limited forward chaining as soon as possible. One of the possible ways to do this is by waiting until the end of the rule node traverse for starting the propagation, as nonpropagated facts are currently handled. Anyway, the newly entered information could be accessed during the node traverse under action.

Another desirable feature is to change the formerly given information. The propagation of the changes will be done with the aid of the concepts and rules already instantiated and of the history of value alterations. For each altered value, if it is an instantiated concept, it is necessary to access the corresponding instantiated hierarchies and to alter those nodes. It is also necessary to find the rules where the value could have been used for an inference and check if the inference is still holding. These control features are already available and will be tested in this modified environment.

The explanation about the reasoning may be requested at any point where the user is asked about an evidence, requiring the analysis of the rule chaining. The status of the hypothesis base may be checked if a summary of the observations and of the partial conclusions is needed. A limited form of explanation can already be obtained during the interruptions.

The Dipmeter Advisor system (Smith, 1984) for well-log interpretation helps geologists to define hydrocarbon reservoir structure, using dipmeter patterns combined with knowledge of local geology and rock properties. Its knowledge base comprises about 90 rules, like (8) below, partitioned according to their function; these rules are applied in a forward-chaining manner and the results are stored in a layered blackboard. The system also includes an user interface with graphical facilities.

```
IF
 there exists a delta-dominated continental-
       shelf marine zone and
 there exists a sand zone intersecting the
       marine zone and
 there exists a blue pattern within the
       intersection
THEN
 assert a distributary far zone
  top     <-- top of blue pattern
  botton  <-- bottom of blue pattern
  flow    <-- azimuth of blue pattern        (8)
```

Although a complete listing of the knowledge base was not available at the time this paper was written, it seems feasible to reproduce the system's behavior and expressive power. The forward chaining and the representation by rules are already implemented; the assignment shown in the right-hand side of the rule in (5) requires a kind of computable predicate where the values of some arguments are assigned from other existing values.

Litho (Bonnet and Dahan, 1983), a system for interpretation of oilwell measurements, is a descendent of the Dipmeter Advisor system, and one of its versions was written in EMYCIN. It uses knowledge from geologists (coded in about 500 rules and in hierarchies for petrography and paleontology) and takes into account the fact that many logs should be analyzed in detail and that the identification of rocks is context-dependent, due to some rocks that have similar log responses (which limit statistical approaches to the interpretation of geological data). The nature of the domain, where data may be contradictory and where the inferences are considered to be weak, forced an emphasis on certainty factors combination functions. The user can complete the feature extraction (done by pattern recognition techniques for detecting activity, presence of plateaus, ramps, beds and layers) if he realizes that some event was not detected.

Seismic interpretation, whose main use is to find potential oil and gas traps, is another promising area for knowledge-based systems. It is considered as "the interface between the exact mathematics of seismic data processing and the inexact geological reasoning" (Denham, 1984). It is predicted that improvements in seismic data interpretation will require more "intelligence"; in this sense, the future systems will be of greater usefulness to consultants that nowadays do this work.

The analysis of earth monitoring satellite images is an area for which attention was directed by AI research in recent years. Applications include analysis of land use, change detection, and context dependent feature extraction, among others. A source of application of AI techniques under consideration is that related to computer vision and scene analysis; in this sense, some works using this approach will be commented.

The problems related to unsupervised classification of agricultural segments have also been recognized as suitable for the application of AI techniques (Swain, 1985). Signature extension could probably benefit if knowledge about the environment were taken into account; layered classifiers also likely to be improved or even substituted by the techniques in focus, and the treatment of spatial information is still a challenge for the researchers due to its importance and complexity.

The recognition of man-made objects, such as vehicles and buildings in natural scenes, as done by Kim et al. (1984), utilizes various kinds of knowledge (contextual, domain specific and picture specific) that are kept separated from the inference engine, and are stored in frames (with object hierarchy, rules for confidence evaluation and procedures for evidence seeking). The control mechanism is distributed over the objects of the system. The same kind of scenes and the same amount of knowledge may be represented in the implemented model (in a different form), although the control is distributed and the representation model is different. This kind of applications shows how a diversified representation combined with a complex control structure can be useful for seeking specific objects.

The expert system developed by CCRS to update forestry maps with LANDSAT data (Goldberg et al., 1985) took into account the handling of contextual information in order to cope with limitations of image processing techniques. It interfaces an image processing system and has knowledge about the available algorithms and the interpretation of the results. Expert modules were built for the general problem of updating maps, for cloud and shadow detection, for verifying geometric properties, for detecting change and others. The structure of communicating experts around a set of blackboards cannot be directly represented by the implemented system; however, one possible solution is to use the conditions for accessing the list of alterations in order to communicate among knowledge modules (expressed by decision rules, for instance).

Tentative approaches to improve low-level processing by knowledge-based methods were attempted, but the results attained so far, although encouraging, are not definitive. The rule-based image segmentation system of Levine and Nazif (1985) defined strategies for dynamic rule ordering by classifying the rules into sets.

The interpretation of airport aerial images by Spam (Mckeom et al., 1985) uses image-to-map correspondence (via camera models) for generating cartographic coordinates and a rule base for generating expectations from image-processing results and for selecting the next task to perform. The domain-dependent spatial constraints restricts the hypothesis formation. This later feature is suitable when dealing with other types of images.

Some extensions to the descriptive power of images are intended to be done, such as an increase in the maximal available resolution, to 1024x1024, and the generalization of pyramid usage, currently restricted to an envelope generation algorithm; for the advantages and drawbacks of pyramid structures, see Tanimoto (1980) for instance; Bajcsy and Rosenthal (1980) present a system using this structure. Another class of alterations refers to some known low-level processing algorithms, like convolution operations and noise filtering. The possibility of representing declarative and procedural knowledge offers a flexible tool for implementing knowledge-based systems for this area.

4. CONCLUSIONS

Several known intelligent systems for geology, remote sensing and image analysis were analyzed in detail, in order to detect the necessary alterations to be inserted on the implemented representation and control modules of INPE's system. This analysis will be of help for defining the features of new versions of the system.

Some restricted form of natural language processing for acquiring information and generating explanations also seems desirable. Another desirable feature is an interface to a graphical facility to help the visualization of data and of partial conclusions.

The proposed alterations are intended to generated a computerized assistant for the professionals in the related areas in order to help them in their data analysis.

5. REFERENCES

BAJCSY, R.; ROSENTHAL, O.A. Visual and conceptual focus of attention. In: TANIMOTO, S.L.; KLINGER, A., ed. *Structured computer vision: machine perception through hierarchical computation structures.* New York, Academic, 1980, p. 31-55.

BARR, A.; FEIGENBAUM, E.A., ed. *The handbook of Artificial Intelligence.* Stanford, CA, Heuristech Press, 1981. v. 1.

BARR, A.; FEIGENBAUM, E.A., ed. *The handbook of Artificial Intelligence.* Stanford, CA, Heuristech Press, 1982. v.2.

BONNET, A.; DAHAN, O. Oil-well data interpretation using expert system and pattern-recognition technique. In: INTERNATIONAL JOINT CONFERENCE ON ARTIFICIAL INTELLIGENCE, 8., 1983. *Proceedings.* IJCAI, p. 185-189.

DENHAM, L.R. Seismic interpretation. *Proc. of the IEEE*, 72(10):1255-1265, 1984.

DUDA, R.O.; HART, P.E.; NILSSON, N.J.; REBOH, R.; SLOCUM, J.; SUTHERLAND, G.L. *Development of a computer-based consultant for mineral exploration; annual report.* Menlo Park, CA, Stanford Research Institute, 1977.

FINDLER, N.V., ed. *Associative networks: representation and use of knowledge by computers.* New York, Academic, 1979.

GASCHNIG, J. *Development of uranium exploration models for the PROSPECTOR consultant system; final report.* Menlo Park, CA, Stanford Research Institute, 1980.

GOLDBERG, M.; GOODENOUGH, D.G.; ALVO, M.; KARAM, G.M. A hierarchical expert system for updating foretry maps with Landsat data. *Proceedings of the IEEE*, 73(6):1054-1063, 1985.

HANSON, A.R.; RISEMAN, E.M., ed. *Computer vision systems.* New York, Academic, 1978.

HAVENS, W.S.; MACKWORTH, A.M. Schemata-based understanding of hand-drawn sketch maps. In: BIENNIAL CONFERENCE OF THE CANADIAN SOCIETY FOR COMPUTATIONAL STUDIES

ON INTELLIGENCE, 3., Victoria, BC, 1980. *Proceedings*. p. 172-178.

HAYES-ROTH, F. Knowledge-based expert systems. *Computer*, 17(10): 263-273, 1984.

KIM, J.H.; PAYTON, D.W.; OLIN, K.E. An expert system for object recognition in natural scenes. In: CONFERENCE ON ARTIFICIAL INTELLIGENCE APPLICATIONS, 1., Denver, CO, 1984. p. 170-175.

LEVINE, M.D.; NAZIF, A.M. Rule-based image segmentation: a dynamic control strategy approach. *Computer Vision, Graphics, and Image Processing*, 32(1):104-126, 1985.

McKEOWN, D.M.; HARVEY, W.A.; McDERMOTT, J. Rule-based interpretation of aerial imagery. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 7(5):570-585, 1985.

MOONEYHAN, D.H. The potential of expert systems for remote sensing. In: INTERNATIONAL SYMPOSIUM ON REMOTE SENSING OF ENVIRONMENT. 7., Ann Arbor, MI *Proceedings*. 1983, p. 51-64.

NAVON, D. Forest before trees: the precedence of global features in visual perception. *Cognitive Psychology*, 9:353-383, 1977.

NAU, D.S. Expert computer systems. *Computer* 16(2):63-85, 1983.

OHTA, Y. *A region-oriented image-analysis system by computer*. Dr. Eng. Thesis, Kyoto, Dept. of Info. Sci., Kyoto Univ., 1980.

QUILLIAN, M.R. Semantic memory. In: MINSKY, M., ed. *Semantic information processing*. Cambridge, MA, MIT Press, 1968. p. 227-270.

SIMONI, P.O. *An approach for associative networks with application to scene analysis*. Doctoral Thesis, São José dos Campos, INPE, Mar. 1986, in press. (original in Portuguese).

SIMONI, P.O.; RENNA e SOUZA, C. Scene analysis using knowledge stored in associative networks. In: SEMINÁRIO INTEGRADO DE SOFTWARE E HARDWARE, 10., Campinas. *Proceedings*. SEMISH, 1983, p. 415-424. (original in Portuguese).

SMITH, R.G. On the development of commercial expert systems. *The AI Magazine*, 5(3):61-73, 1984.

SWAIN, P.H. Advanced interpretation techniques for earth data information systems. *Proceedings of the IEEE*, 73(6): 1031-1039, 1985.

TANIMOTO, S.L. Image data structures. In: TANIMOTO, S.L.; KLINGER, A., ed. *Structured computer vision: machine perception through hierarchical computation structures*. New York, Academic, 1980, p. 31-55.