A HYBRID FORMALISM FOR REPRESENTATION AND INTERPRETATION OF IMAGE KNOWLEDGE

Francisco de Assis Tavares Ferreira da Silva
Instituto Nacional de Pesquisas Espaciais - INPE
Caixa Postal 515 - Sao Jose dos Campos - SP - Brazil
E-mail: inpenco§brfapesp.bitnet

ABSTRACT

A blackboard-base knowledge representation, adapted to maintain information about meteorological radar images using method of frame, is proposed. This representation is to be used as a basis for the development of artificial intelligence applications to help human operators in the task of interpreting radar images and related informations. This project is part of the development of a laboratory for artificial intelligence applications in the image processing area.

KEY WORDS: Artificial Intelligence, Expert System, Image Interpretation, Radar, Remote Sensing Application

1. INTRODUCTION

The radar image representation, analysis and interpretation process exhibits characteristics which make it a good candidate for automatization using artificial intelligence techniques [1]-[5]: (i) the task demands specialized knowledge, (ii) the specialists can describe the used methods, (iii) the methods can be described with symbols, (iv) the interpretation demands heuristic solutions, and, finally, (v) the task is neither trivial nor excessively difficult [6].

The analysis and interpretation process involves different knowledge levels, where the processing varies from pixels to the symbolic representations of the possible image interpretations of the many regions of the image, associated to entities of the real world [7,8]. The higher levels of representation, that is, the levels where the information is already symbolic in the sense of being more abstract, may integrate information from elsewhere beyond the information extracted from the image itself [1,9].

The use of artificial intelligence methods and techniques may increase the efficiency and productivity of the interpretation process. Note that image interpretation being a dynamic process and dependent of the available image type is based if the system disposes of some ability to learn [10,11].

The present work proposes the development of a formalism to represent the knowledge associated to the images and their possible interpretations, as well as a set of methods which permit the manipulation of these knowledges. To test the applicability of this formalism the development of a radar image interpretation aid system is proposed.

The proposed formalism uses a knowledge base structured according to the frames' method [12], combined with some of the semantic nets' characteristics [13]. A review about Hybrid Knowledge Representation can be seen in Bittencourt [14]. The symbolic structure of the objects of interest presented in a given image is represented through frames structures, involving meanings associated to a specific interpretation, which are represented through links similar to the ones used in semantic nets. An analog combination of representation methods can be seen in the ERNEST system [15] where emphasis was given to the semantic nets structures.

Using the proposed formalism it is possible to represent from the original images pixels (in the proposed experimental application a radar image) to the symbolic interpretation of the physical phenomena under analysis. The higher levels of representation also integrate foreign information, independent of the image, and provenient from, say, a geographical data bank, data collection platforms, satellite images, profiles, meteorological balloons, avionics or another radar.

The paper is organized in the following way: in section 2 the frame model is briefly presented; in section 3 the language developed for the frames management is presented and how this language can be used in the image interpretation automatization process is commented; in section 4 the radar images characteristics and how the images will be represented using the frame model are discussed; in section 5 the Blackboard model is briefly presented; in section 6 the radar image interpretation process is presented showing how it can be helped by the use of Knowledge Sources acting on the proposed representation; finally, in section 7, conclusions and future research directions are presented.

2. THE FRAME MODEL

Frames were introduced as a generalization of the semantic nets in order to express the internal structure of objects, mantaining the possibility of representing properties' heritage in the same way as the semantic nets [16].

The fundamental ideas of this method were introduced by Marvin Minsky (1975) in his paper "Framework to Represent Knowledge" [12]. The applications proposed by Minsky for the new method were scene analysis, visual perception modelling and natural language understanding; however, the paper proposes neither an implementation methodology nor a formal definition of the method. Since 1975, many

systems were implemented based on the frames idea and many formal definitions were proposed. Usually a frame consists in a set of attributes which, through their values, describe the characteristics of the object described by the frame. The values belonging to these attributes may be other frames, generating a network of dependencies between the frames. The frames are also organized in a specialization hierarchy, creating another dependency dimension between them. The attributes also have properties regarding the type of values and restrictions on the number of them which they can have. These properties are called facets.

The systems based on the method of frames are not an homogeneous set, however some fundamental ideas are shared by them. One of these is the concept of property heritage, which permits the specification of an object class through the declaration that this class is a subclass of another one that has the property in question. Heritage can be a very efficient inference mechanism in domains which show a natural taxonomy of concepts.

Another idea common to the systems based on frames is the expectative guided reasoning. A frame contains attributes, which can be tipical values, or a priori values, the so called default values. When trying to instantiate a frame so that it corresponds to a given situation, the reasoning process should fill the values of the frame attributes with the available information in the situation description. The fact that the reasoning process knows what to look for to complete the necessary information, and in case it is not available, which tentative values to attribute to the empty attributes may be a fundamental factor for the efficiency recognition of a complex situation.

Many of the method's representation power depends on this inclusion of expectatives and assumptions. The default values may be very useful in the representation of general information, more usual cases and ways to make generalizations.

The default values are freely associated to their corresponding attributes, such that they may easily be substituted by new items which better fit the current situation. In fact they can serve as "variables" or special cases of "reasoning", frequently permitting the dismissal of logic quantifiers.

A third idea is the procedural link. Apart from the default values, an attribute may be associated to a procedure which must be executed when certain conditions are satisfied, for example: when the attribute is created; when its value is read, changed or destroyed.

The link, by heritage, through attributes' values, or an interrelated frames set's procedural link allows certain specific inferences to be made efficiently which can be used to control the changes in the focus of attention and emphasis of the application.

For the analysis of visual scenes, the different frames of a system describe the scene from different points of view, and the transformations between one frame and another represent the effects of movement from one place to another. For non visual types of frames, the differences between the frames of a system may represent actions, cause and effect relations, or changes of the viewpoint. Different frames of a system may share the same attribute values, and this is the critical point that makes it possible to coordinate united information from different viewpoints.

Since a frame is proposed to represent a situation, a process of correspondence of patterns tries to associate values to each frame attribute, consistent with these attributes' facets. The correspondence process is partly controlled by information associated to the frame (which includes information about how to deal with susprises) and partly by knowledge about the objectives of the system in course. These are important uses of the information obtained when a correspondence process fails. This may be used to select an alternative frame which better fits in the situation.

3. MANAGEMENT OF THE FRAMES

The manipulation of the structure of frames which constitutes the knowledge base will be made through a data manipulation language developed in PROLOG language [17].

The characteristics and functionalities of the language are presented in the following:

(i) Frames' hierarchies, in the form of "trees", permitting the heritage of attribute values.

(ii) Encapsulation of the frames and the relations between them, through primitives which permit the entities of the language to be manipulated.

(iii) Procedural linking of PROLOG functions defined externally to frames attributes. These functions are activated when an attributed value is desired to be found and it is not available.

(iv) Possibility of an attribute's value to be the name of a frame.

The primitives of the frame manipulation language may be classified into the following groups: Visualization and initialization primitives, definition primitives, attribution primitives, elimination primitives and search primitives. The objectives of each group of primitives is presented in the following.

- Initialization and Visualization Primitives

Permit the initialization of the hierarchy top frame and the system diverse control variables, beyond offering resources for visualization of the frames, their attributes' values and the heritage hierarchy.

- Definition Primitives

Permit the definition of new frames in a certain heritage hierarchy position, and the definition of a given frame's new attributes.

- Attribution Primitives

Permit an attribute value or a procedural link to be associated to a given frame.

- Elimination Primitives

Permit elimination of attributes, their values and associated functions.

- Search Primitives

These are the language central primitives, they permit navigation inside the heritage hierarchy, through consultation to the relations of descendency between the diverse frames, and the recovery of attribute values.

The recovery of an attribute is made through a search, initially made in the starting frame. In case the attribute or its value are defined in this frame the search continues according to the frame hierarchy. If the attribute is defined, but not its value, and if there is an associated function, this function is called with the following parameters: (frame), (attribute), (result). "result" is a variable which should return the result. This result becomes the attribute value of the frame where the search is and ends. A "type" parameter informs us how the value was obtained and if it is a frame or not. The possible types are:

value-value directly obtained from attribute.

frame-value is a name of frame obtained directly from attribute.

function-value - value obtained through a function call

function-frame - value is a name of frame obtained through a function call.

The proposed language should help from the acquisition of pattern and semantic relations task to the image interpretation process itself.

Heuristics for knowledge acquisition will be implemented via a man-machine interface, which through the proposed language permits frames to be built containing the necessary knowledge for the diverse interpretations. A review of this process for knowledge acquisition is presented by Oliveira [18] and an example of this process is presented by Silva et al. [19].

The interpretation process uses frame manipulation methods, that is, a given inference method [6] may use the primitives of the language for creation, manipulation and deletation of the frames inside the interpretation process.

4. REPRESENTATION OF RADAR IMAGES

Meteorologic radar images are composed of point clusters (stains) which generate the radar map (PPI: Plan Position Indicator, RHI: Range-Height Indicator, CAPPI: Constant Altitude Plan Position Indicator among others [20]). In this map, we can identify geographic elements, which may be subtracted, and meteorological phenomena (targets) like clouds, rain, wind, snow, hail or others. The return signal intensity is shown in many discrete levels (digital image), called slices, where the number of levels depends on the calibration of the radar spectral band and on the density of the detected element. Usually the sampling can be preprogrammed, permitting delineation of areas and vertical section sampling with many levels of intensity quantification. A general and historical review of the meteorological radar system characteristics is presented in "Radar in Meteorology" [21].

The representation to be adopted in the implemention of the Knowledge Base will be based on frame structures. A review of the clustering process is presented in Mussio and Pawlina [22]. A general review of the computational models for image representation is presented in Argialas and Harlow [4].

Each frame of the representation proposed contains attributes whose values can be stored directly in the structure or determined through procedures. An important characteristic of the frame structure is that frames lower in hierarchy can inherit values of attributes from frames higher in hierarchy.

Typically a frame corresponding to an image will be represented by a set of attributes. The attribute of lowest level is the pixel, which is a mapping from the image point coordinates to its gray level. Other attribute values may be obtained through preprocessing routines: filtering, segmentation and classification. Other attributes will be used at levels of greater abstraction, where it becomes possible to identify the elements of the image interpretation.

This representation will permit the use of several heuristics to program automatic alerts for targets we may want to observe. It should also be useful in the creation of heuristics for pre-selected target phenomena, evolution (historic behaviour) and automatized storing. The general architecture of the proposed representation is shown in figure 1.

The first level corresponds to the analysed region. The second level instances the class which represents the possible vision types of each cell under analysis (see figures 1, 2.a and 2.b). This description is obtained from the processing of the original image corresponding to the pixel matrix (coordinates and gray levels), generated by the radar control processor. The next levels present the evolution of phenomena and attributes like: intensity, width, height, length, and area of each cell, beyond baricenter and elliptic factor of each cell or subcell extracted from the original image (see figures 2.d, 2.e and 2.f).

The information stored in the frames that form the Blackboard (Figure 3) belong to different levels of information. The first level corresponds to the original image representation (coordinates and gray levels), this information is obtained directly from the radar control processor. The second level contains elements retrieved from the original image used by the Knowledge Sources to validate the prospective targets. The third level corresponds to attributes obtained through preprocessing and context analysis. These attributes are generated by the respective Knowledge Sources. The following levels will contain intermediate information generated and used by the Knowledge Sources during the interpretation process.

The intermediate informations, linked to the results produced by the Knowledge Sources, may also be information specific levels. The intermediate result structure is linked to the intermediate conclusions of the classification or interpretation tasks' successive improvement process.

The Blackboard will contain also frames corresponding to structures of events, recording the whole processing. Some examples of events are modifications representing transformations or movements which occur to the elements analysed.

The structure of frames forming the Knowledge Base will be manipulated by many Knowledge Sources defined in a hierarchical way. These Knowledge Sources are based in different processing methods according to their specialities, varying from production rules to image processing algorithms.

A set of reference frames will be defined for each standard image element. These reference frames can be useful when interpreting new images.

The flexibility of the frame structure permits other informations, linking different images or describing procedure groups that act on the images, to be represented in the Blackboard. The interrelation between these different types of knowledge will be generated, mantained and modified by a set of Knowledge Sources, each one specialized in a task.

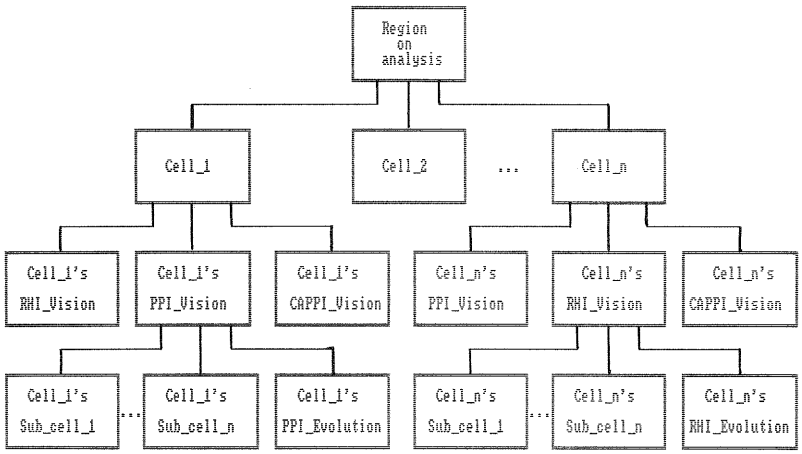

Fig. 1. Hierarchy of the frames

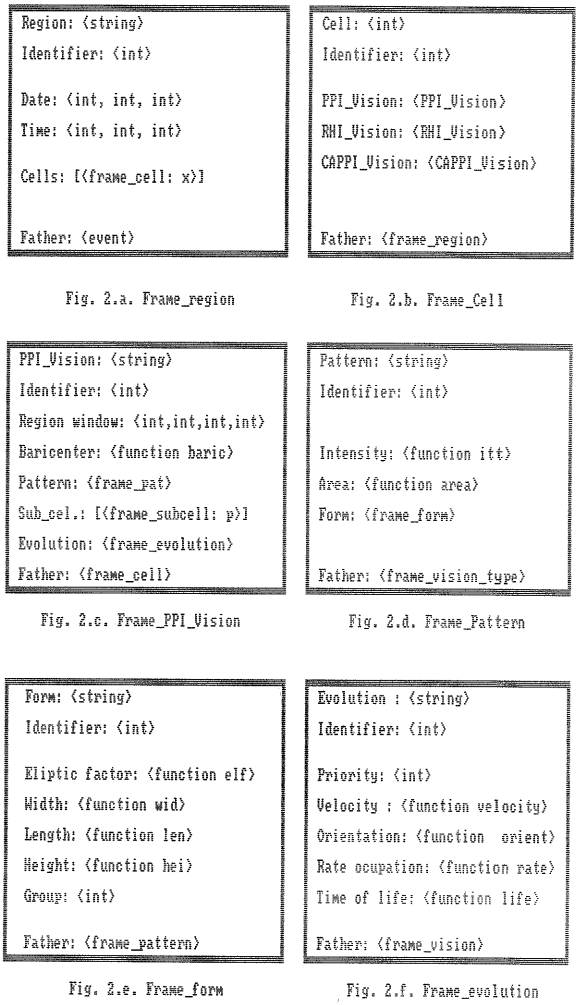

Fig. 2.a. Frame_region

Fig. 2.b. Frame_Cell

Fig. 2.c. Frame_PPI_Vision

Fig. 2.d. Frame_Pattern

Fig. 2.e. Frame_form

Fig. 2.f. Frame_evolution

Fig. 2 - Specific Frames

5. THE BLACKBOARD MODEL

The basic structure of the Blackboard consists of a data structure called Knowledge Base and entities called Knowledge Sources [5] and [23]-[25].

The Knowledge Sources alter the Knowledge Base. There is no centralized flux control: the Knowledge Sources are autonomous. The Knowledge Sources are active entities that may contain from algorithms to rule based expert systems, even another Blackboard.

The informations about the solution problem's solution state are stored in the Knowledge Base of the system. There the Knowledge Sources make alterations which take the system incrementally to the solution of the problem.

The Knowledge Sources answer opportunistically to the alterations on the Blackboard. There is no specific control element in the Blackboard model. The model specifies a generic environment for the problem's solution. The control may be in the Knowledge Sources, Knowledge Base, separate modules or in some combination of these three.

The architecture proposed can be seen in the figure 3. The principle of working of the presented system can be observed through the interpretation process (next section).

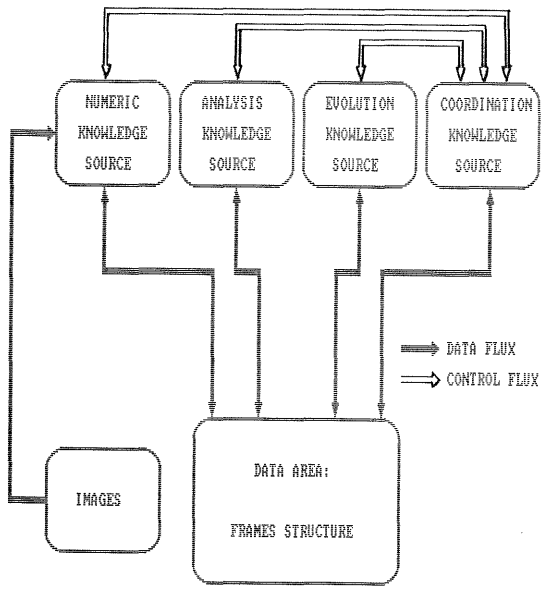

Fig. 3. System Architecture

6. THE INTERPRETATION PROCESS

The interpretation process may be divided in two basic levels: (i) meteorological targer qualification, which is the identification of some image element such as rain, when the qualification, or selective classification, will be related to the rain area and density information extraction; (ii) phenomena evolution, in the case of rain being information like intensity, propagation speed and duration.

The first Knowledge Source (numeric KS in figure 3) is responsible for the quantification of the image elements.

This source consists of a set of numeric procedures capable of generating new attribute values for a given image, given available attributes. Some functions of this Knowledge Source are: calculus of the number of elements; quantification and storage of the sub cells of each element; calculus and storage of the average intensity level of each analysed element; calculus and storage of the distance between each element. These elements may be then confirmed through context analysis: verification of the other elements in the scene, distance between elements and analysis through context rules.

The function of the second Knowledge Source (analysis KS) is to process the reference frames to identify the analysed frame components, using the information stored in the selected reference frames.

The third Knowledge Source (evolution KS) updates the history of the analysed elements and eventually the reference frame information or generates new frames of this kind.

The fourth Knowledge Source (coordination KS) manages the different information generated by the other sources and the schedule of tasks to be performed. This source signals indicating what should be done with the analysed frame, for example: ignore it, store the image and the frame, fire some alert signal, update the schedule, etc.

The coordination source also incorporates a set of control auxiliary modules to monitor the alterations on the Blackboard information, and to activate one or more Knowledge Sources according to information about the next tasks on the schedule.

7. CONCLUSION

The Blackboard model has been used before in the image processing area. Goodenough et al. (1987) introduced an aplication based on the Blackboard model in the area of Remote Sensing [5]. Shihari et all. (1987) use this architecture in the area of post address identification [24]. Andress and Kak (1988) use the technique in the geometric image area [25]. Matsuyama (1987) uses the model in an aplication towards aerial image understanding [9].

The knowledge representation proposed in this work will be used initially inside a prototype expert system for meteorological radar images cataloging. Also the efficacy of the diverse heuristics proposed by the experts in these image's interpretation for meteorological phenomena recognition will be investigated.

Our perspective is to also explore the connectionist aspect through use of functional neural networks as specific knowledge sources.

This project is part of a more ambicious project regarding the design of an artificial intelligence tools based environment for the development of aplications in the image interpretation area.

This project involving three departments at INPE intends to develop applications concerning not only radar but also satellite, aerial and medical images. The knowledge representation proposed in this paper will be used as a prototype for the representation to be integrated in this environment.

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