Visual knowledge modelling and related interpretation problem-solving method

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Abstract

Imagistic domains require from the problem-solver the ability of applying primarily visual recognition of objects, and only secondarily search and analytical methods in order to interpret these objects. Most of the time, the visual recognition process is developed at the sensorial level and has no related conceptualisations. This work explores the use of ontologies and introduces the concept of visual chunk, as a modelling primitive applied to elicit and represent visual objects in complex domains. A problem-solving method is defined to describe the reasoning process of object recognition and interpretation. Based on this method, a full knowledge system application was developed and is being used to support the interpretation of sedimentary rocks through petrographic analysis.

Keywords: Knowledge Engineering, Ontology, Problem-solving method, Sedimentary rock interpretation.

1 Introduction

Imagistic domains [1] can be described as a set of activities in which the solution of some task depends on the recognition of visual stimuli through the environment, which is then applied to support the problem-solving method in some abstract cognitive level. Traditional examples of this kind of domain include satellite image interpretation, X-ray and other medical image interpretation, fault detection in industrial products and most of the tasks related with Geology.

Solving problem in such domains is a two-stage process. The first stage refers to the collection of relevant evidence through the domain. Although this process can be related to the sensorial level, the recognition and selection of relevant evidence are not only a pattern recognition operation. As first demonstrated by De Groot [2] with chess experiments, and later on confirmed by many other investigators, [3-5] the collection of visual evidences is a symbolic process supported by knowledge about the domain. Indeed, a person cannot see what he/she does not know.

The collection of evidence starts with the recognition of geometric patterns in the domain at the low level visual system. These patterns are decomposed and combined in many different forms (applying the aptitude that was called by Sternberg [6] creative ability) in order to match with some previously known object stored in the memory. This matching is not a pattern matching (in the sense that is not a geometric correlation of features) but a sort of conceptual matching.

During the problem examination, an abstract representation of objects in the domain is extracted from the image and compared with the internal representation of the same kind of objects. These cognitive structures have no conceptual translation (i.e. they have no name) and are part of the expert tacit knowledge, which are hardly extracted using traditional knowledge acquisition techniques [7]. The low level abstraction of geometric stimuli combinations, which we call here visual chunk, is a fundamental support of the inference process in imagistic domains. The importance of visual chunks in the image interpretation was recognized through a study carried out with 19 geologists in three different phases, described in [8]. Consistently, the novices applied the names and proportion of simplified domain concepts, while the experts described the image using interpreted features. The experiment was reproduced with the diagnosis of plant diseases in agriculture, with similar results. The experts clearly recognised more complex features in the problem than the ones the novices reported. These features only could be seen if a short inference process would be developed in order to extract such meanings.

The collection and application of visual chunks are an essential characteristic of expertise in imagistic domains, but the elicitation and representation of these objects are not a trivial task. The knowledge acquisition techniques are intended to collect and organize conceptualisations, and not tacit knowledge. Therefore, in many knowledge acquisition experiments, the importance and the use of sensorial chunks to support inference during the problem-solving process are not even made evident, and the domain knowledge model results incomplete and inefficient.

This paper describes an approach to externalise (with the meaning of transforming tacit knowledge in explicit knowledge) [9] and represent visual chunks using cases and the ontology of the domain, to fill the gap between the tacit and explicit knowledge. It also formalizes the problem-solving method, which describes the interpretation process supported by visual chunks and domain knowledge. Finally, it describes a symbolic algorithm to support interpretation of sedimentary rocks in the domain of Petrography, which demonstrates the viability of the proposal.

2 Visual Knowledge Modelling

A combination of case analysis and ontologies has shown to be a powerful knowledge acquisition approach to externalise the tacit knowledge, represented by visual chunks and their relation with the desired interpretations in image-based reasoning applications. Cases are representative of the kind of problems that are needed to be solved in the domain and, also, allow a fast comprehension about the types of information used to support the problem-solving methods. This information is structured through an ontology, that is, a formal and explicit specification of a shared conceptualisation [10], applied to formally describe the concepts and relationships that can exist in the domain.

The knowledge modelling approach for image-based reasoning applications proposed in this work starts with a case-based analysis. A set of case descriptions (for example, some medical report or rock description) is analysed to identify which domain concepts are used by experts in describing images. These symbolic concepts can be confronted with the vocabulary extracted from the experts through knowledge acquisition techniques, and a final set of selected concepts is defined, which are revised by the expert. Therefore, this knowledge modelling view makes use of a symbolic approach of image description and interpretation, as opposed to the numeric approaches oriented by geometric feature-based image representations. The ontology of the image-based domain can be firstly proposed from this set of concepts.

The approach suggests that the cases shall be used to guide the interviews with the expert in order to identify the reasoning process developed in the image-based interpretation tasks. The expert is requested to indicate, in the image descriptions, which concepts identify the domain features that support the interpretation described in the solution part of the case. This procedure makes evident when the ontology does not include the description of the relevant features, and allows the expert to define and include the concepts that describe the visual chunks that he could ascribe to the image. In our work, we concluded that there is a relevant gap that must be treated between the information that is described and the one that really supports inference (Figure 1).

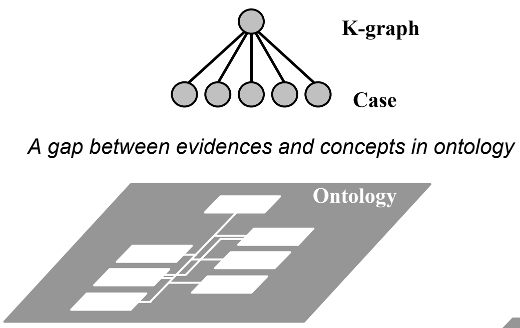
Sandstones are the most important sedimentary rocks as petroleum reservoirs and water aquifers, and therefore their petrographic description and interpretation can be considered as a mature domain, such as clinical analysis or Medicine. This maturity was achieved through the formalisation of an extensive technical vocabulary and a methodology to develop descriptions of the problems in the domain. The technical vocabulary is intended to allow the communication within the domain, independently of the level of expertise of the agents involved in problem solving, and moreover describes the domain in terms of geometric objects, or explicitly known features. These objects comprise partially or totally the sensorial chunks applied for inference. For these domains, it is possible to elicit the relationship between the concepts in the ontology and the cognitive objects applied for inference. We propose that the explicit establishment of this problem-solving assumption can enable the development of reasoning mechanisms in real cases of image-based interpretations.

In this project, in order to adapt the relationship between the domain ontology and visual chunks employed in the effective reasoning process, we propose the use of a formalism of knowledge acquisition and graphic representation, called knowledge graphs (or K-graphs) [11]. A K-graph is a AND/OR tree in which:

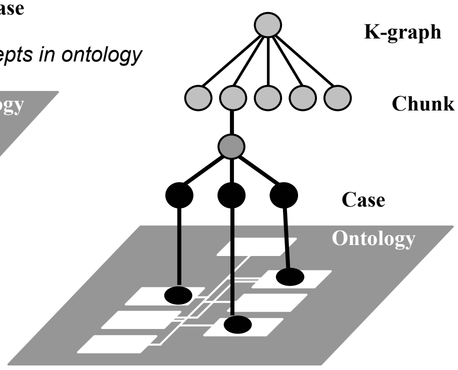
- the root node represents the interpretation hypothesis;
- the leaf nodes represent the visual chunks pointed by the experts in the image, as the evidence to support the conclusion. These nodes are ordered by their influence in defining inference and can be combined (i.e., considered together) to increase these influences and the certainty of the interpretation achieved.

This resource is used to identify any eventual gap between the leaves of the K-graphs and the previous defined ontology (Figure 1a):

In a further stage, the expert can be invited to fill the gap, defining the relationship between each of the evidences described in the K-graphs and the concepts of the ontology, creating a third level of nodes formed also by AND/OR trees. This third level describes how the concepts of ontology are combined to compose the evidence (Figure 1b), representing an explicit adaptation process required to the modelling process. When necessary, new concepts can be included and the evidence can also be nominated. This approach allows us to introduce the visual chunks as a new abstract concept type, defined as an aggregation of geometric features described into the domain ontology.



a) The concepts applied in the image description are not the same used to justify the inference



b) A third level in the K-graph define the relationship between visual chunks and concepts in the ontology

Figure 1. Filling the gap between the information that is described and the one that really supports inference

This approach was validated in the domain of Petrography, where we carried on a set of experiments to acquire cases, as well as the ontology and visual chunks applied for image-based rock interpretation. 25 full rock descriptions (which qualified around 130 attributes of the rock samples) were analysed to identify the domain concepts employed by geologists in petrographic descriptions. These domain concepts were confronted with the vocabulary extracted through interviews, protocol analysis and classification techniques with the experts. A final step of reviewing the selected rock concepts was developed with the petrology expert. According to the oil reservoir interpretation task, the domain ontology was organised in a part-of hierarchy with the structure recognised in the studied cases.

The rock description cases available are used to guide the interviews with the petrology expert in order to summarise the reasoning process developed in the rock interpretation of sandstones and to fill the gap between the concepts described into the ontology and the geological features related with each interpretation.

The recognition of visual chunk as a cognitive resource to support inference strongly influences the way in which imagistic domains should be analysed during the knowledge engineering process. We proposed here a formal tool to identify and externalise these objects, in order to make their role in the inference process clear. The next section describes how these concepts are formalised in the knowledge models [12].

3 The Knowledge Specification

This project was developed with special attention to a structure-preserving design issue, following the guidelines of CommonKADS methodology, [12], which means that information content and structure present in the knowledge model are preserved in the final architecture of knowledge system (KS). The visual knowledge was acquired and represented in the knowledge level, [13] which specifies in detail the domain concepts applied to support interpretation. The implementation level allows describing how this concepts and interpretation are related to software components.

3.1 The Domain Knowledge

The domain schema is a description of the abstract concepts and relationships in a domain. The instances, by their side, can be expressed as tuples of concept-attribute-values or any logical combination of concept-attribute-values (CAV), which are, in this work, called *terms of the domain* (or *domain expressions*).

We propose that a domain schema to represent visual knowledge can be organized through three conceptual types:

- Concept: describes the objects that occur in the application domain. The characteristics of one concept are defined through a set of attributes and restrictions imposed to the values of the attributes.
- Relation: defines how concepts are organized to form the domain hierarchy and some special defined relations among concepts that support inference.
- K-graph: expresses the relation between instances of visual knowledge concepts and the possible image interpretations modelled [13].

K-graphs applied to visual knowledge modelling can play the role of the rule-type in defining the inference paths of the problem-solving process. They can be built as an AND/OR tree, where the root represents the interpretation and the leaves are instances of visual chunks. A set of weights also must be assigned to each chunk using some numeric scale according to inference requirements. A weight means the relevance of the chunk to the interpretation in some image-based reasoning domain, but other type of relevance criteria also can be employed to represent knowledge about uncertainty.

The way that K-graphs are applied is not implicit in the knowledge representation. K-graphs just represent how much each feature influences the choice of that interpretation as a solution for the reasoning problem. These K-graphs indeed define all the possible routes of the inference in the KS.

Visual chunks are visual knowledge concepts described in the model as a logical combination of domain instances indicated by the expert, and each instance representing a term of domain. This concept has the fundamental role in this image-based reasoning model, of mapping (or adapting) the expert level knowledge (the tacit knowledge expressed as visual chunk) to a novice level of knowledge, represented by the simplified (or geometric) domain concepts. Chunks also allow applying the expert level inference over a problem described in novice or intermediate level of expertise by users.

The logical combination of simplified domain concepts which builds a visual chunk can be described as an AND/OR tree. According with this AND/OR tree approach of knowledge modelling, a set of visual features that must be found in the image is grouped together with an AND operator, forming an AND domain expression. In contrast, an expression grouped by an OR operator means that at least one visual knowledge concept of the group needs to be found in the image.

In the petrographic domain, the K-graphs that describe rock interpretation represent the relation between instances of geological features and possible rock interpretations. The visual chunks were modelled with terms of the domain described as a logical combination of instances of geological features, easily recognised by an intermediate level petrographer and described through geometric aspects (color, size, texture). These features are modelled as domain concepts. The Figure 2 shows an example of a visual chunk in the petrographic application called Dissolution. This chunk is composed by domain concepts such as

Macroporosity with Location = Intersticial AND Macroporosity with (Paragenetic Relation = Dissolution of Fe-Calcite) OR (Paragenetic Relation = Dissolution of Fe-Dolomote/Ankerite) OR (Paragenetic Relation = Dissolution of Siderite).

The rock interpretation K-graphs make explicit the inference paths of the rock interpretation process, where the root represents the rock interpretation and the leaves are AND/OR trees of visual chunk instances of rock sample images. Weights were assigned to each rock chunk using a scale of 1 to 6, meaning the relevance of the chunk to the rock interpretation. Figure 2 depicts the representation of a chunk nominated by the expert as Dissolution, which is part of the K-graph called *Telodiagenesis Under Meteoric Conditions*, and influences this conclusion with weight 3, along with four other chunks, with, respectively, weights 5, 5, 5 and 3.

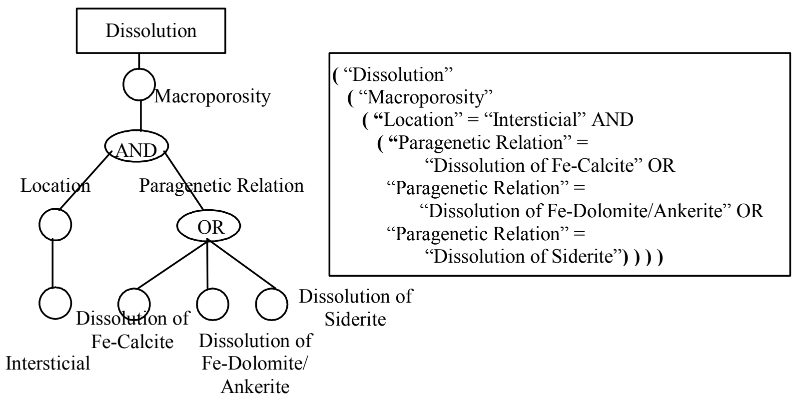


Figure 2. A simplified visual chunk built as a logical combination of geological domain concepts

Each rock interpretation represented by a K-graph is associated with a threshold value, which indicates the minimum amount of evidences that someone needs to find out in the problem, in order to suggest with some confidence that a suggested interpretation is correct. The threshold and values for chunks was extracted in two phases of knowledge acquisition: the first phase was necessary to define some "scale" where the expert could express his feelings about confidence and influence, and a second phase where the scale was filled with thresholds and weights. A diagenetic environment imprints their characteristics on the rock in more than one aspect, and so the more aspects are found in the rock sample image, the most probably the interpretation is correct. That assumption can be assumed for many visual knowledge domains. Although there were some initial differences among the thresholds defined for each interpretation, the expert considered acceptable to this domain to define a standard value of 6 for all K-graphs in that scale of chunks, which leads to find at least two chunks or more to indicate a single interpretation.

K-graphs associated with ontologies, extracted from cases, are efficient and potentially reusable tools to acquire and model visual knowledge in complex domains. The more mature the domain is in developing a shared description vocabulary, the more useful will be a tool like this in extracting tacit knowledge. Our model is built with 26 abstract concepts, 6 distinct relation (where *part-of* is the structural relationship) and 6 K-graphs, which refer 33 chunks. 113 different attributes with respective domains are defined to characterize the full set of concepts.

3.2 The Problem-Solving Method

The identification of human reasoning strategies applied in the image-based interpretation is not a trivial task, even after identifying which relation (such as those represented in K-graphs) defines the paths of inference. In tasks that apply visual knowledge, some cognitive skills that support the reasoning simply cannot be reproduced and still remain not understood [14]. However, a rationalization of the tacit visual knowledge used by the expert can be proposed as a model, in the knowledge level [15], structuring the main concepts of the usable and effective inference methods required to KS development.

According to [8], the skill involved in the image-based reasoning development of interpretation tasks can be understood as the matching of visual chunks, which allows the selection of special regions of the mental schema that will be examined by analytical methods. The initial chunk matching is fundamental to select a possible interpretation by the expert.

According to this rational analysis of the interpretation process, the expert conducts a visual analysis of the image, picking up a set of sensorial stimuli from a part of the image. At the same time, he/she identifies from the set of known visual chunks those that can be associated with the particular kind of analyzed image. The image is successively compared to each of the visual chunks, until the whole image was examined and the interpretations indexed by chunks were selected. Further process of validation chooses one as the most probably correct interpretation to the image. This human reasoning rationalization can be modelled as a problem-solving method (PSM).

A PSM describes the use of knowledge and data required for an inference process in a more abstract and structured way [16]. These methods are abstract models of inference processes applied in solving a particular class of problem, [17] such as diagnosis, classification or configuration. In our work, we propose the visual interpretation PSM which models the sequence of inference steps and the knowledge roles and data required during the reasoning process in a KS. Figure 3 presents the inference structure of the visual interpretation PSM, represented in CommonKADS formalism [12].

A possible sequence of the reasoning shown in the Figure 3 starts with a case description, provided by the user and further decomposed in the related concept-attribute-value (CAV). A set of CAV is selected from the visual chunks, according to the K-graph which is being analyzed first. The similarity between both patterns is evaluated. The value is compared to the threshold associated with the K-graph that is being analysed. If the value is above the threshold, the present K-graph will be validated and it will specify the interpretation. The inference is repeated while there are chunks and K-graphs to be analysed.

In the petrographic domain, the visual interpretation PSM is applied to suggest a diagenetic interpretation (i.e., explain the process of post-depositional evolution and consolidation) of sandstones from the visual geologic features described by an intermediate level petrographer. In [18] it has been shown the competence, operational description and requirements/assumptions that define a visual interpretation PSM usable in the petrographic domain, but also reusable in other application domains.

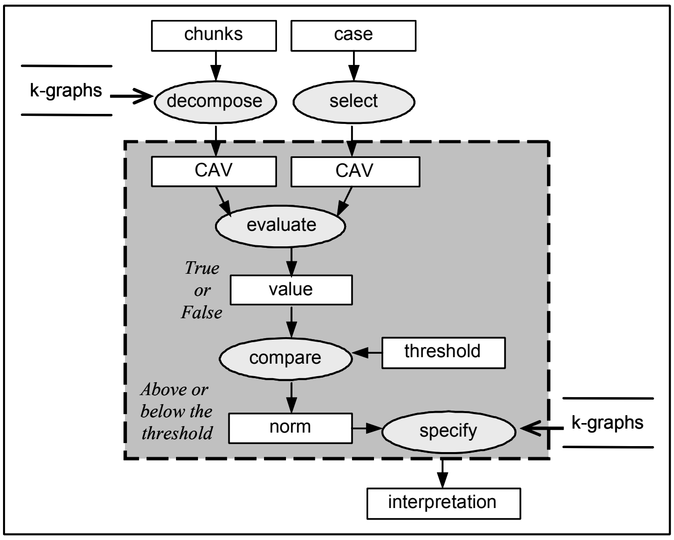


Figure 3. The visual interpretation PSM

4 A Knowledge and Data Inference Algorithm for Rock Interpretation

In order to present a practical validation of the visual interpretation PSM, an inference component for rock interpretation task was developed and integrated to an intelligent database application called *PetroGrapher*. The system was developed to manage knowledge and data resulting of petrographic descriptions of oil reservoir rocks. The interpretation mechanism consists of a symbolic inference algorithm that reproduces the reasoning of the expert, keeping the structural correspondence with the knowledge level rationalization of this image-based reasoning process.

The task is fully supported by the petrographic ontology, which is dynamically managed by an application-oriented interface. This interface provides the user with the technical vocabulary (in the intermediate level) of visual rock features, thus supporting the correct and complete description of a rock sample. When the rock sample description is accomplished, the data about the rock sample is stored in the application database, and the user can initiate the inference process. The application database keeps the user instances of ontological concepts, while knowledge database stores the knowledge instances and their association with solutions, that is, the K-graphs. The interpretation algorithm collates the K-graphs on the stored rock sample data in the database, trying to validate one of the modelled interpretations.

The inference algorithm retrieves the K-graphs about rock interpretation from the knowledge database1 to a working memory. Once in the working memory, each K-graph is selected and decomposed in rock chunks. Then, one chunk is selected for matching. This selected chunk is decomposed in its geological features, adjusting the information granularity to the data described in the rock sample. The rock features are searched as required in the modelled domain expressions: if the algorithm fetches a set of evidences grouped by an AND operator, it must find all the features in the application database, in contrast of fetching a set grouped by an OR.

A chunk is validated (or activated) when all its domain expressions are found in the description. If the sum of weights of the whole set of activated chunks is greater than the K-graph threshold, the rock interpretation associated with the K-graph is confirmed. The algorithm will try for alternative interpretations until there were no more description data to be compared. Since that a rock can be subjected to more than one diagenetic environment during its formation, the inference process can find more than one interpretation. In order to justify the conclusion reached for the user, the algorithm stores the knowledge and data paths examined to achieve the interpretation.

The algorithm was validated using a set of cases described by an expert petrologist. Besides, the expert had analysed the inference path to adjust the weights and thresholds of the chunks and K-graphs. The efficiency of the inference mechanism is limited by the user capacity to recognise and describe the diagnostic features in the sample under analysis. Non-expert geologists may not be able to recognise specific diagnostic rock features, therefore limiting the applicability of this inference algorithm. The system is now being submitted to this test, so it is not clear how the degree of expertise can influence in the capacity of getting interpretation. Even so, according to the expert, any suggestion of correctly derived interpretation is a useful insight for such a complex task as the interpretation of oil reservoir rocks.

5 Conclusions

The study of expert skills in an imagistic domain has demonstrated that experts develop a variety of representations for the visual objects in the domain. One of these representations has shown to be directly related to the high level of expertise: the visual chunk. A visual chunk is an abstraction of a set of sensorial stimuli, which are seeing repeatedly in the domain, associated with some special solution or interpretation, and represented in the mental schema of the expert. Since their first definition in chess representations [2], visual chunks have been recognised in many different image-based reasoning domains [7]. Visual chunks play an important role in guiding the inference process, by holding links with the internal mental schema of knowledge.

The visual chunk was proposed in this project as the primitive for representing the tacit knowledge effectively applied in the image-based interpretation. The domain ontology extracted from the case analysis does not contain these concepts, since they are not used in the normal transference of explicit knowledge. The representation of visual chunks has the important role of filling the gap between the intermediate knowledge level described into the ontology and the expert knowledge applied in the inference.

The chunks are modelled as an aggregation of concepts previously described in the ontology. In the other hand, they are associated to the solution through knowledge graphs, which allow considering the individual influence of specific chunks in suggesting the interpretation.

The combination of ontology, chunks and K-graphs is explored by a PSM, which models the successive attempts over the declarative knowledge to search for a reasonable interpretation for the user case.

The association of K-graphs and case analysis has shown to be a practical and effective tool to externalise and acquire the declarative knowledge represented as concepts of ontology and causal relations of the domain. These concepts and relations were not evident in elicitation sessions conducted on a traditional knowledge-acquisition basis. The approach is reusable in any well-structured domain which demands image-based interpretation.

The domain model, in this work, expresses the knowledge over two levels: the externalisation level, which describes the concepts at an intermediate (between novice and expert) stage of expertise; and the expertise level, which models the tacit knowledge of the expert. A set of formal modelling tools was proposed to support the knowledge acquisition and the inference in some image-based domain. Finally, to demonstrate a practical application of this work, an application called *PetroGrapher* was implemented, and is being used to operationally support petrographic analysis.

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