Model-Based Image Interpretation under Uncertainty and Fuzziness

Isabelle Bloch

Institut Mines-Telecom - Telecom ParisTech - CNRS LTCI - Paris, France
isabelle.bloch@telecom-paristech.fr

Abstract. Structural models such as ontologies and graphs can encode generic knowledge about a scene observed in an image. Their use in spatial reasoning schemes allows driving segmentation and recognition of objects and structures in images. The developed methods include finding a best segmentation path in a graph, global solving of a constraint satisfaction problem, integrating prior knowledge in deformable models, and exploring images in a progressive fashion. Conversely, these models can be specified based on individual information resulting from the segmentation and recognition process. In particular models relying on spatial relations between structures are relevant and more flexible than shape models to be adapted to potential variations, multiple occurrences, or pathological cases. The problem of semantic gap is addressed by generating spatial representations (in the image space) of relations initially expressed in linguistic or symbolic form, within a fuzzy set formalism. This allows coping with uncertainty and fuzziness, which are inherent both to generic knowledge and to image information. Applications in medical imaging and remote sensing imaging illustrate the proposed paradigm.

Keywords: Image understanding, structural models, graphs, spatial relations, fuzzy modeling, model-based segmentation and recognition, constraint satisfaction problems.

1 Structural Models

Models constitute an important source of information for image understanding, that provides generic knowledge, complementary to the actual data and images. Such models may provide information regarding the objects contained in the scene, as well as their spatial arrangement. This aspect confers them a structural nature, in which spatial relations are of prime importance.

Let us consider medical image interpretation as an example. On the one hand, biological, anatomical or biomechanical models can be used to guide image interpretation. On the other hand, medical images can be exploited in order to build models of the human body, from an anatomical or functional point of view.

Iconic representations of anatomical knowledge can be found, such as anatomical atlases. Although their use for normal structure recognition is well acknowledged, they remain difficult to exploit in pathological cases. Anatomical

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knowledge is also available in textbooks or dedicated web sites, and expressed mainly in linguistic form. These models involve concepts that correspond to anatomical objects, their characteristics, or the spatial relations between them. Human experts use intensively such concepts and knowledge to recognize visually anatomical structures in images. This motivates their use in computer aided image interpretation. Some attempts to formalize this knowledge have been performed, in particular in the form of ontologies (e.g. the Foundational Model of Anatomy [14]). Such linguistic or ontological descriptions can be found in other domains, such as remote sensing.

In several applications, shape is not a sufficient information to describe a scene, and models should involve higher level information, on the structure and spatial arrangement of the scene. Hence models of spatial relations have to be developed and included in the models. Graphs are often used to represent the structural information in image interpretation, where the vertices represent objects or image regions (and may carry attributes such as their shapes, sizes, and colors or grey levels), and the edges carry the structural information, such as the spatial relations among objects, or radiometric contrasts between regions.

In our work, we concentrate mainly on spatial relations, which are strongly involved in linguistic descriptions. We proposed mathematical models of several spatial relations, in the framework of fuzzy set theory [5]. Fuzziness is very important to model the intrinsic imprecision of spatial relations expressed in a linguistic way. The modeling relies on tools from mathematical morphology [7,9], which provides a strong algebraic framework. This allows deriving similar models, with the same properties, in various settings, either quantitative, semi-quantitative (fuzzy) or qualitative (logics) ones (see [6] for mathematical details), and thus reasoning at different levels and on different types of information. In particular, the fuzzy representations can enrich anatomical ontologies [21] and contribute to fill the semantic gap between symbolic concepts, as expressed in the ontology, and visual percepts, as extracted from the images. A symbolic concept representing a given spatial relation can be translated into semi-qualitative representation using the proposed fuzzy models. The parameters are tuned using learning procedures for each application domain[1] [3], leading to a representation in the image domain. Combination with image information can then be performed. These ideas were used in particular in our segmentation and recognition methods.

Interactions between models and images can be seen in different directions. A model can drive the exploration of an image, as described next. Conversely, the result of an image interpretation process can be used to modify a generic model to make it specific to the observed case. Moreover, results on several images can help building generic models. In the sequel, we focus on the first aspect.

[1] For instance, a relation such as "close to a given object" is intrinsically fuzzy, and moreover its concrete meaning depends on the domain. It is typically not the same for anatomical structures in medical images, and for man-made or natural objects in satellite images.

2 Model-Based Structure Recognition and Image Understanding

The methods we developed for segmentation and recognition of 3D structures in medical images can be seen as spatial reasoning processes. Two main components of this domain are spatial knowledge representation and reasoning.

In particular spatial relations constitute an important part of the knowledge we have to handle, as explained before, since they constitute relevant information to guide the recognition of structures embedded in a complex environment, and are more stable and less prone to variability (even in pathological cases) than object characteristics such as shape or size. Imprecision is often attached to spatial reasoning in images, and can occur at different levels, from knowledge to the type of question we want to answer.

The reasoning component includes fusion of heterogeneous spatial knowledge, decision making, inference, recognition. Two types of questions are raised when dealing with spatial relations:

1. given two objects (possibly fuzzy), assess the degree to which a relation is satisfied;
2. given one reference object, define the area of space in which a relation to this reference is satisfied (to some degree).

In order to answer these questions and address both representation and reasoning issues, we rely on three different frameworks and their combination:

- mathematical morphology, which is an algebraic theory that has extensions to fuzzy sets and to logical formulas, and can elegantly unify the representation of several types of relations;
- fuzzy set theory, which has powerful features to represent imprecision at different levels, to combine heterogeneous information and to make decisions;
- formal logics and the attached reasoning and inference power.

The association of these three frameworks for spatial reasoning is an original contribution of our work, and the lattice structure underlying each of these frameworks is a core feature, making the use of mathematical morphology relevant and powerful [6].

The interpretation of complex scenes in images often requires (or can benefit from) a model of the scene. The spatial arrangement of objects or structures is often crucial for differentiating among objects with similar appearances in the images, or disambiguating complex cases. Examples occur in many domains, including medical imaging, in which structural knowledge can help in the interpretation of the images. In magnetic resonance imaging (MRI), for instance, radiometry is often insufficient for recognizing individual anatomical structures, and their relative spatial configuration provides an important input into the recognition process [12]. Other examples occur in aerial and satellite imaging, robot vision, and video sequence interpretation, among other fields.

In our work, we often address the image interpretation problem as a joint problem of image segmentation and object recognition, based on structural information. The methods summarized in the next section address this question, and belong to a more general class of model-based or knowledge-based interpretation systems. Only a sketch of each of them is provided here, and mathematical and technical details can be found in the mentioned references.

3 A Few Approaches

3.1 Morphisms between Graphs

A first recognition approach, called global, uses the first type of question (1). The idea is to represent all available knowledge about the objects to be recognized. A typical example consists of graph-based representations. The model is then represented as a graph where nodes are objects and edges represent links between these objects. Both nodes and edges are attributed. Node attributes are characteristics of the objects, while edge attributes quantify spatial relations between the objects. A data graph is then constructed from each image where the recognition has to be performed, based on a preliminary segmentation into homogeneous regions. Each region of the image constitutes a node of this data graph, and edges represent spatial relations between regions, as for the model graph. The comparison between representations is performed through the computation of similarities between model graph attributes and data graph attributes. Note that it might not be straightforward to design an appropriate similarity function involving vertex and edge attributes for a specific application.

Although graph representations have become popular in the last 40 years [13], a number of open problems remain in their efficient implementation. In particular, when expressing the recognition problem as a graph matching problem between the image and model graphs, which is an annotation problem, this scheme often requires solving complex combinatorial problems [13]. Improvements can be achieved by suppressing iteratively inconsistent annotations using a constraint propagation procedure, as proposed e.g. in [29,36] for simple geometrical figures or in [24,32] for the annotation of image segmentations. However, the constraint propagation procedure does not guarantee a unique annotation. Moreover, all of these approaches assume a correct initial segmentation of the image. However, the segmentation problem is a known challenge in image processing, to which no universal solution exists. The segmentation is usually imperfect, and no isomorphism exists between the graphs being matched. An inexact matching must then be found, for instance by allowing several image regions to be assigned to one model vertex or by relaxing the notion of morphism to that of fuzzy morphism [10,28]. For example, previous studies [15,16] employ an over-segmentation of the image, which is easier to obtain. A model structure (i.e. a graph vertex) is then explicitly associated with a set of regions, and the recognition problem is expressed as a constraint satisfaction problem. To overcome the complexity issue, a weaker version of the model relations (encoded in the edges) is considered, and the problem is solved using a modified AC-4 propagation algorithm [25].

3.2 Progressive Exploration of the Image Using Graphs

A second type of approach relies on the second type of question (2), and is called here progressive or sequential [8,12,18]. In this approach, objects are recognized sequentially and their recognition makes use of knowledge about their relations with respect to other objects. This sequential segmentation framework allows decomposing the initial problem into several easier-to-solve sub-problems, using the generic knowledge about the scene. Relations with respect to previously obtained objects can be combined at two different levels of the procedure. First, fusion can occur in the spatial domain, using spatial fuzzy sets. The result of this fusion allows building a fuzzy region of interest in which the search of a new object will take place, in a process similar to focalization of attention, thus driving the image exploration. In a sequential procedure, the amount of available spatial relations increases with the number of processed objects. Therefore, the recognition of the most difficult structures, usually handled in the last steps, will be focused in a more restricted area. Another fusion level occurs during the final decision step, i.e. segmentation and recognition of a structure. For this purpose, spatial relations are introduced in the evolution scheme of a deformable model, in which they are combined with other types of numerical information, usually edge and regularity constraints.

This approach, as pointed out in [12], requires to define the order according to which the objects have to be recognized and the choice of the most appropriate order is a challenging issue. This was addressed in [18], with two original contributions:

- First, we extended the sequential segmentation framework by introducing a pre-attentional mechanism based on saliency [22], which is used, in combination with spatial relations, to derive a criterion for the optimization of the segmentation order.
- Secondly, we introduced criteria and a data structure which allow us to detect the potential errors and control the ordering strategy.

The proposed framework has two levels. The first level is a generic bottom-up module which allows selecting the next structure to segment. This level does not rely on an initial segmentation or classification, but instead on a focus of attention and a map of generic features. The sequential approach allows this level to use two types of knowledge: generic and domain independent features in unexplored area of the image to segment, and high-level knowledge such as spatial relations linked to the already recognized structures. The selection criterion is used to optimize the segmentation order and to select the next structure to segment at each step. The second level achieves recognition and segmentation of the selected structure, as well as the evaluation of the segmentation. The recognition of the structure is achieved at the same time as the segmentation. This level is composed by the segmentation method defined in [12], integrating spatial relations in a deformable model, and an original evaluation method. It uses two types of a priori information: the spatial information which allows us to reduce the search area, and a radiometric estimation of the intensity of the structure.

Therefore, the radiometric estimation needs to discriminate the intensity of the structure only in the search area and not in the whole image. Once a structure is segmented and recognized, this level also evaluates the quality of the result and proposes a strategy to guarantee the spatial consistency of the result and to potentially backtrack on the segmentation order.

This approach is illustrated in Figure 1.

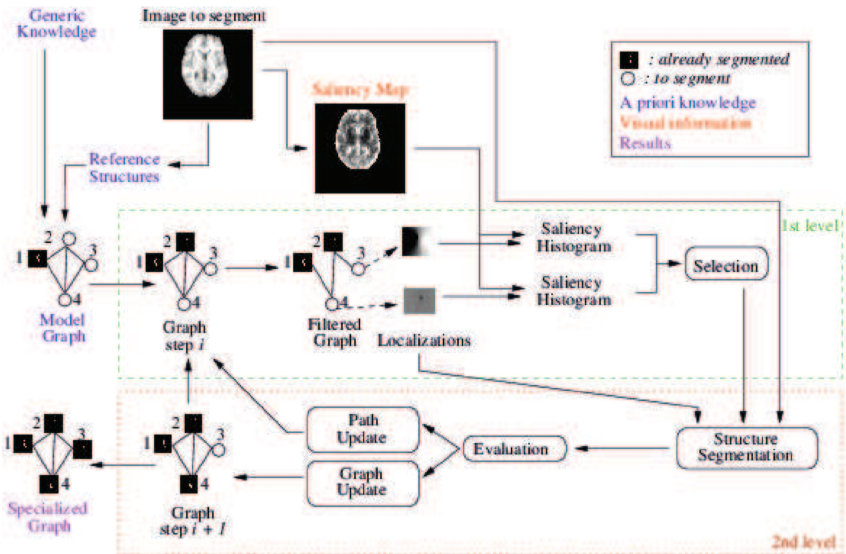

Fig. 1. General scheme of the sequential segmentation framework (figure reproduced from [18]). The graph initially represents only the generic knowledge (here about the brain) and the reference structures. At each step, a structure is selected according to the saliency of its localization and its relations to other structures. This structure is then segmented and the result is evaluated. In case of success, the graph is updated and the process is iterated until the graph is completely specialized or no more structure can be segmented. In case of failure, the system is constrained to select another path to segment and the process is iterated.

3.3 Global Method Based on Graphs and CSP

To overcome the problems raised by sequential approaches while avoiding the need for an initial segmentation, we proposed in [27] an original method that still employs a structural model, but solves the problem in a global fashion. Our definition of a solution is the assignment of a spatial region to each model object, in a way that satisfies the constraints expressed in the model. We propose a progressive reduction of the solution domain for all objects by excluding assignments that are inconsistent with the structural model. Constraint networks [30] constitute an appropriate framework for both the formalization of the problem and the optimization. An original feature of the proposed approach is that the regions are not predetermined, but are instead constructed during the reduction process. The image segmentation and recognition algorithm therefore differs from an annotation procedure, and no prior segmentation of the image into meaningful or homogeneous regions is required. This feature overcomes the limitations of many previous approaches (such as [15,16]). More precisely, a constraint network is constructed from the structural model, and a propagation algorithm is then designed to reduce the search space, which is an adaptation of AC-3 algorithm [30] with an ordering of constraints to reduce the computational cost and reduce the domains as much as possible. Finally, an approximate solution is extracted from the reduced search space. Once the propagation process terminates, the solution space is typically reduced substantially for all of the model structures. The final segmentation and recognition results can then be obtained using any segmentation method that is constrained by this solution space.

This approach is illustrated in Figure 2.

3.4 Global Method Based on Nested Conceptual Graphs and Fuzzy CSP

In this section, we summarize a hybrid method, relying on a preliminary segmentation of the image, which does not need to be perfect, and on a recognition step to identify the concepts represented in the model [33]. In some applications, for instance to interpret Earth observation images, multiple instantiations of some objects should be taken into account (e.g. several boats in a harbor).

In this case, the interpretation relies on a generic model of the scene to be recognized, encoding objects and groups of objects, spatial relations between between objects or between groups, along with the imprecision and uncertainty attached to the formal representations of such relations (this includes complex relations such as alignment, parallelism, etc. [34,35]). The model is formalized as a nested conceptual graph [31], which allows representing internal and external information, zooming, partial description of an entity, or specific contexts. Identifying possibly multiple instances of the model in an image is formalized as a graph homomorphism.

Finding the best homomorphism is performed by solving a fuzzy constraint satisfaction problems (FCSP) [17], using arc-consistency checking [11]. FCSP and arc-consistency checking have been extended in [33] to deal with relations having an arity greater than two and with complex objects. The main contribution in this work concerns the adaptation of the algorithm to deal with groups of objects which can be related among them or have a spatial property such as being aligned. A methodology is then proposed to find the instantiations of a nested conceptual graph in an unlabeled image. Experimental results on high resolution satellite images show that the proposed approach successfully recognizes a given spatial configuration (such as harbor or airport) and is robust to image segmentation errors. The results demonstrate the interest of using complex spatial relations for the interpretation of images.

This approach is summarized in Figure 3.

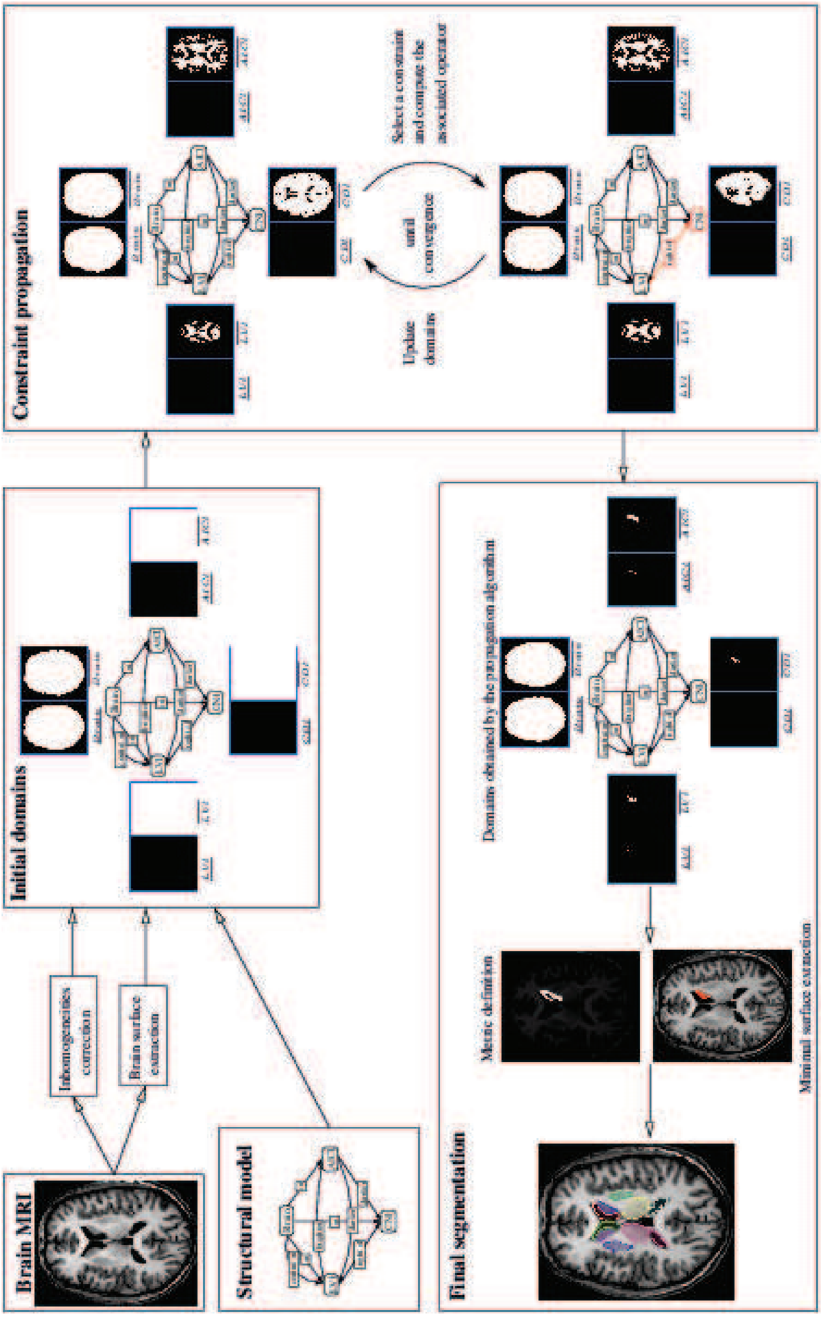

Fig. 2. Overview of the CSP approach for the brain structures example (figure reproduced from [27]). For instance, the solution space of the left caudate nucleus (CNl) is reduced based on the constraint that "the left caudate nucleus (CNl) is exterior (i.e. to the right in the image) to the left lateral ventricle (LVl)".

isabelle.bloch@telecom-paristech.fr

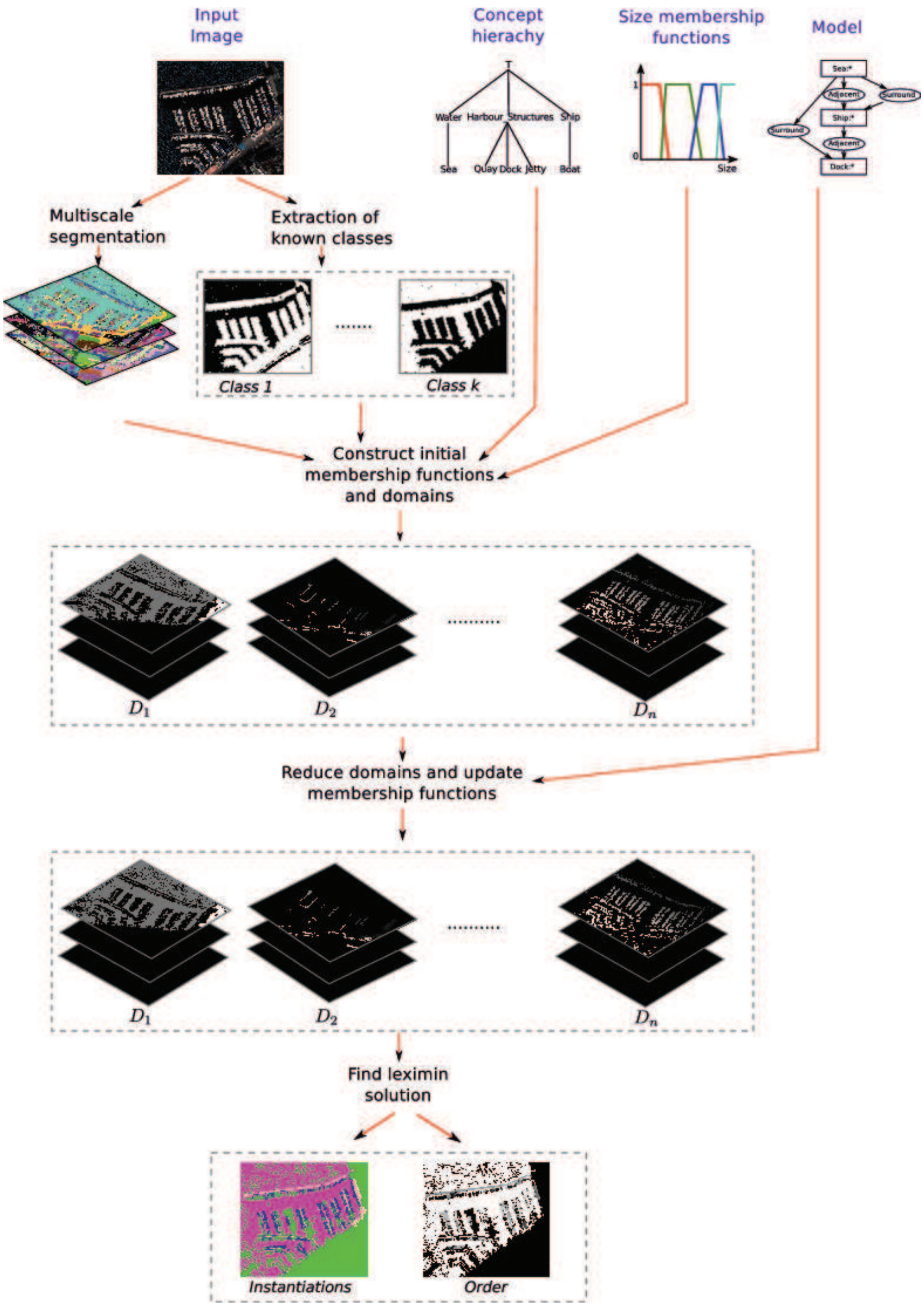

Fig. 3. Summary of the method for determining the model's instantiations using nested conceptual graphs and FCSP (figure reproduced from [33])

4 A Few Examples

The approaches summarized above have been proved useful in a number of applications. A first example concerns brain structure recognition and segmentation in 3D MRI images. Both sequential and global approaches have been successfully applied [12,18,23,27], in particular for ventricles and grey nuclei. These structures highly benefit from the knowledge expressed in a structural model, since spatial relations are quite stable while shape and location are much more prone to inter-individual differences. These relations mainly include adjacency, directional relations and distances. The recognition and segmentation performed well even in the presence of large tumors deforming the normal structures.

Sequential approaches have been also applied in other domains, with sometimes more complex relations. Let us mention two examples:

- optical coherence tomography (OCT) is now used for eye imaging, and provides high resolution images of the retinal layers. In [19,20], a method segmenting all visible layers was proposed, integrating spatial constraints between layers, such as approximate parallelism;
- segmentation of thoracic structures, including pathological ones such as tumors, was performed in [26,37], on 3D CT images. As an example, the heart was segmented using shape and structural information, modeling the fact that it is approximately between the lungs.

In all these examples, the global organization of the structures, and in particular their relative orientation, was known. It could then easily be used, knowing the orientation of the acquired images. When considering ante-natal images, this is no more true, since the position of the fetus can vary (while the position of the pregnant woman during the acquisition is known). This question was addressed in [1,2,4], and a progressive exploration of the images allows deriving both the global orientation and the recognition of individual structures.

Let us finally mention an application of the FSCP method summarized in Section 3.4 to the problem of finding harbors in high resolution remote sensing images [33], based on a conceptual graph. Several instantiations of the model are then searched for in the image, and here more complex relations, considering also groups of objects, are used.

These examples will be illustrated during the conference.

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[2] `http://perso.telecom-paristech.fr/~bloch/tii/staff.html`

isabelle.bloch@telecom-paristech.fr

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isabelle.bloch@telecom-paristech.fr