On the interest of spatial relations and fuzzy representations for ontology-based image interpretation

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In this paper we highlight a few features of the semantic gap problem in image interpretation. We show that semantic image interpretation can be seen as a symbol grounding problem. In this context, ontologies provide a powerful framework to represent domain knowledge, concepts and their relations, and to reason about them. They are likely to be more and more developed for image interpretation. A lot of image interpretation systems rely strongly on descriptions of objects through their characteristics such as shape, location, image intensities. However, spatial relations are very important too and provide a structural description of the imaged phenomenon, which is often more stable and less prone to variability than pure object descriptions. We show that spatial relations can be integrated in domain ontologies. Because of the intrinsic vagueness we have to cope with, at different levels (image objects, spatial relations, variability, questions to be answered, etc.), fuzzy representations are well adapted and provide a consistent formal framework to address this key issue, as well as the associated reasoning and decision making aspects. Our view is that ontology-based methods can be very useful for image interpretation if they are associated to operational models relating the ontology concepts to image information. In particular, we propose operational models of spatial relations, based on fuzzy representations.

Keywords: Image interpretation, semantic gap, ontology, spatial relations, fuzzy sets, fuzzy relations, brain imaging.

1. Introduction

The literature acknowledges several attempts towards formalization of some domains. For instance in medicine, noticeable efforts have led to the development of the Neuronames Brain Hierarchy[c] and the Foundational model of anatomy (FMA)[d] at the University of Washington, or Neuranat[e] in Paris at CHU La Pitié-Salpêtrière. Generic formalizations of spatial concepts were also developed and specified in different fields, for spatial reasoning in artificial intelligence, for Geographic Information Systems, etc.

In a parallel domain, well formalized theories for image processing and recognition appeared in the image and computer vision community.

Noticeably, both types of developments still remain quite disjoint and very few approaches try to use the abstract formalizations to guide image interpretation. The main reason is to be found in the so called "semantic gap", expressing the difficulty to link abstract concepts with image features. This problem is also related to the symbol grounding problem.

In this paper we highlight a few features of the semantic gap problem in image interpretation. We show that semantic image interpretation can be seen as a symbol grounding problem in Section 2. In this context, ontologies provide a powerful framework to represent domain knowledge, concepts and their relations, and to reason about them. Therefore, they are likely to be more and more developed for image interpretation. We briefly explain the potentials of ontologies towards this aim in Section 3. A lot of image interpretation systems rely strongly on descriptions of objects through their characteristics such as shape, location, image intensities. However, spatial relations are very important too, as explained in Section 4, and provide a structural description of the imaged phenomenon, which is often more stable and less prone to variability than pure object descriptions. We show that spatial relations can be integrated in domain ontologies. Because of the intrinsic vagueness we have to cope with, at different levels (image objects, spatial relations, variability, questions to be answered, etc.), fuzzy representations are well adapted and pro-

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[c] `http://braininfo.rprc.washington.edu/`
[d] `http://sig.biostr.washington.edu/projects/fm/AboutFM.html`
[e] `http://www.chups.jussieu.fr/ext/neuranat`

vide a consistent formal framework to address this key issue, as well as the associated reasoning and decision making aspects. This question is addressed in Section 5. Our view is that ontology-based methods can be very useful for image interpretation if they are associated to operational models of spatial relations (and other concepts), in particular based on fuzzy representations. These operational models contribute to reduce the semantic gap. We provide some hints on this integration in Section 6.

As a typical application where all these issues are raised, we illustrate our purpose with examples in brain image interpretation.

2. Semantic gap in image interpretation and symbol grounding

The **symbol grounding problem** has been first introduced in artificial intelligence by Harnad in [1], as an answer to the famous Searle's criticisms of artificial systems [2]. It is defined in [1] through the fundamental question: *How is symbol meaning to be grounded in something other than just more meaningless symbols.* As underlined in the literature, symbol grounding is still an unsolved problem (see e.g. [3]).

In the robotics community, this problem was addressed as the **anchoring problem** [4]: a special form of symbol grounding needed in robotic systems that incorporate a symbolic component and a reasoning process. The anchoring process is defined as the problem of *creating and maintaining the correspondence between symbols and sensor data that refer to the same physical object.*

In our case, artificial systems are not robotic systems but image interpretation systems. As the former, they incorporate a symbolic component. Some similarities between *Anchoring* and *Pattern Recognition* have been underlined in [5], in order to assess the potentiality of using ideas and techniques from anchoring to solve the pattern recognition problem and vice versa. Similarly, we argue that image interpretation could greatly benefit from such a correspondence. Indeed, the image interpretation problem can be defined as the automatic extraction of the meaning of an image. The image semantics cannot be considered as being included explicitly in the image itself. It rather depends on prior knowledge on the domain and the context of the image. It is therefore necessary **to ground** the digital representation of an image (*perceptual level*) with the semantic interpretation that a user associates to it (*linguistic level*). In the image indexing and retrieval community, this problem is called the **semantic gap problem**, i.e. *the lack of coincidence between the information that one can extract from the visual data and the interpretation of these data by a user in a given situation* [6].

Our view is that image interpretation can be seen as a symbol grounding problem, i.e. the dynamical process of associating image data to human interpretations by taking into account the influence of external factors such as the *social environment* (application domain, interpretation goal, ...) or the *physical environment* of the interpretation. Indeed, image interpretation is the process of finding semantics and symbolic interpretations of image content. This problem has the same nature as the physical grounding of linguistic symbols in visual information in the case of natural language processing systems [7,8]. In our case, linguistic symbols are application domain concepts defined by their linguistic names and their definition.

Example: In cerebral image interpretation, concepts can be: ***brain****: part of the central nervous system located in the head,* ***caudate nucleus****: a deep gray nucleus of the telencephalon involved with control of voluntary movement,* ***glioma****: tumor of the central nervous system that arises from glial cells,...*

Rather than being constrained by a grammar and a syntax as in a formal or natural language, the concepts are organized in a semantic knowledge base which describes their semantics and their hierarchical and structural dependencies.

Example: The human brain is a structured scene and spatial relations are highly used in the anatomical brain description (e.g. the ***left thalamus*** *is* to the left *of the* ***third ventricle*** *and* below *the* ***lateral ventricle****).*

This structural component, in the form of spatial relations, plays a major role in image interpretation. This aspect is detailed in Section 4.

Ontologies are useful to represent the semantic knowledge base. They entail some sort of the world view, i.e. a set of concepts, their definitions and their relational structure which can be used to describe and reason about a domain. This aspect is detailed in Section 3.

As underlined by Cangelosi in [9], a symbol grounding mechanism, as language itself, has both an individual and a social component. The individual component called **Physical Symbol Grounding** refers to the ability for a system to create an intrinsic link between perceptions and symbols. The **Social Symbol Grounding** refers to the ability to communicate with other systems by the creation of a shared lexicon of perceptually-grounded symbols. It is strongly related to the research on human language origins and evolution where external factors such as cultural and biological evolution are primordial.

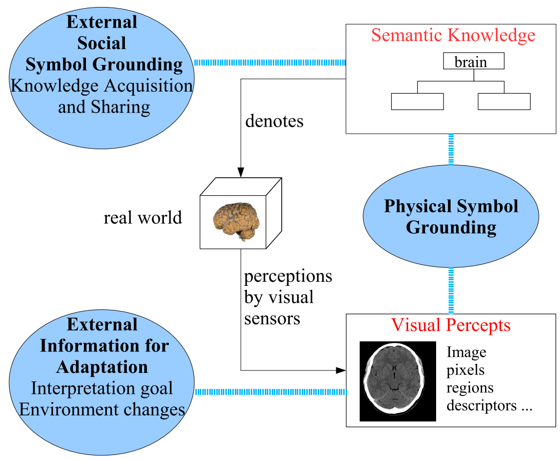


Fig. 1. Physical and external symbol grounding for image interpretation.

In the case of image interpretation systems, these two components of the symbol grounding are also essential and take the following form: on the one hand, the **physical symbol grounding** consists of the internal creation of the link between visual percepts (image level) and a known semantic model of the part of the real world which concerns the application domain (domain semantic level). On the other hand, in order to enable communication and interoperability with humans or other systems, this grounded interpretation must capture a consensual information accepted by a group. As a consequence a **social external symbol grounding component** raises for image interpretation. Moreover, image interpretation systems operate in a dynamic environment which is prone to changes and variations. The interpretation process is highly influenced by external factors such as the environmental context, the perception system or the interpretation goal and it has to adapt itself to these external factors. As a consequence, image interpretation is a distributed and adaptive process between physical symbol grounding and external symbol grounding as shown in Figure 1.

3. Ontologies for image interpretation

In knowledge engineering, an ontology is defined as *a formal, explicit specification of a shared conceptualization* [10]. An ontology encodes a partial view of the world, with respect to a given domain. It is composed of a set of concepts, their definitions and their relations which can be used to describe and reason about a domain. Ontological modeling of knowledge and information is crucial in many real world applications such as medicine for instance [11].

Let us mention a few existing approaches involving jointly ontologies and images. By using ontologies, the physical symbol grounding consists in **ontology grounding** [12], i.e. the process of associating abstract concepts to concrete data in images. This approach is considerably used in the image retrieval community to narrow the semantic gap. In [13], the author proposes to ground, in the image domain, a query vocabulary language used for content-based image retrieval using supervised machine learning techniques. A supervised photograph annotation system is described in [14], using an annotation ontology describing the structure of an annotation, irrespectively of the application domain, and a second ontology, specific to the domain, which describes image contents. Another example concerns medical image annotation, in particular for breast cancer [15], and deals mainly with reasoning issues. But image information is not direcly involved in these two systems. Other approaches propose to ground intermediate visual ontologies with low level image descriptors [16–18], and are therefore closer to the image interpretation problem. In [19], the enrichment of the Wordnet lexicon by mapping its concepts with visual-motor information is proposed.

As the main ontology language OWL is based on description logics, a usual way to implement the grounding between domain ontologies (or visual ontologies) and image features is the use of concrete domains as shown in Figure 2.

Description logics [20] are a family of knowledge-based representation systems mainly characterized by a **a set of constructors** that enable to build complex **concepts** and **roles** from atomic ones. A semantics is associated with concepts, roles and indi-

Table 1. Description logics syntax and interpretation.

Constructor	Syntax	Example	Semantics
atomic concept	A	Human	$A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$
individual	a	Lea	$a^{\mathcal{I}} \in \Delta^{\mathcal{I}}$
Top	$\top$	Thing	$\top^{\mathcal{I}} = \Delta^{\mathcal{I}}$
Bottom	$\perp$	Nothing	$\perp^{\mathcal{I}} = \emptyset^{\mathcal{I}}$
atomic role	r	has-age	$R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$
conjunction	$C \sqcap D$	Human $\sqcap$ Male	$C^{\mathcal{I}} \cap D^{\mathcal{I}}$
disjunction	$C \sqcup D$	Male $\sqcup$ Female	$C^{\mathcal{I}} \cup D^{\mathcal{I}}$
negation	$\neg C$	$\neg$ Human	$\Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$
existential restriction	$\exists r.C$	$\exists$has-child.Girl	$\{x \in \Delta^{\mathcal{I}} \mid \exists y \in \Delta^{\mathcal{I}} : (x,y) \in R^{\mathcal{I}} \wedge y \in C^{\mathcal{I}}\}$
universal restriction	$\forall r.C$	$\forall$has-child.Human	$\{x \in \Delta^{\mathcal{I}} \mid \forall y \in \Delta^{\mathcal{I}} : (x,y) \in R^{\mathcal{I}} \Rightarrow y \in C^{\mathcal{I}}\}$
value restriction	$\ni r.\{A\}$	$\ni$has-child.$\{$Lea$\}$	$\{x \in \Delta^{\mathcal{I}} \mid \exists y \in \Delta^{\mathcal{I}} : (x,y) \in R^{\mathcal{I}} \Rightarrow y = a^{\mathcal{I}}\}$
number restriction	$(\geq nR)$	$(\geq 3$ has-child$)$	$\{x \in \Delta^{\mathcal{I}} \mid \; \lvert\{y \mid (x,y) \in R^{\mathcal{I}}\}\rvert \geq n\}$
	$(\leq nR)$	$(\leq 1$ has-mother$)$	$\{x \in \Delta^{\mathcal{I}} \mid \; \lvert\{y \mid (x,y) \in R^{\mathcal{I}}\}\rvert \leq n\}$
Subsumption	$C \sqsubseteq D$	Man $\sqsubseteq$ Human	$C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$
Concept definition	$C \equiv D$	Father $\equiv$ Man $\sqcap$ $\exists$ has-child.Human	$C^{\mathcal{I}} = D^{\mathcal{I}}$
Concept assertion	$a : C$	John:Man	$a^{\mathcal{I}} \in C^{\mathcal{I}}$
Role assertion	$(a, b) : R$	(John,Helen):has-child	$(a^{\mathcal{I}}, b^{\mathcal{I}}) \in R^{\mathcal{I}}$

viduals using an interpretation $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$, where $\Delta^{\mathcal{I}}$ is a non empty set and $\cdot^{\mathcal{I}}$ is an interpretation function that maps a concept C to a subset $C^{\mathcal{I}}$ of $\Delta^{\mathcal{I}}$ or a role r to a subset $R^{\mathcal{I}}$ of $\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$. **Concepts** correspond to classes. A concept C represents a set of individuals (a subset of the interpretation domain). **Roles** are binary relations between objects. Table 1 describes the main constructors and a syntax for description logics.

Concrete domains are expressive means of description logics to describe concrete properties of real world objects such as their size, their spatial extension or their color. They are of particular interest for image interpretation, as illustrated in Figure 2. Indeed, they allow performing anchoring for a particular application, hence reducing the semantic gap. This grounding approach using description logics and concrete domains has been used by several authors [21,22] for the automation of semantic multimedia annotation.

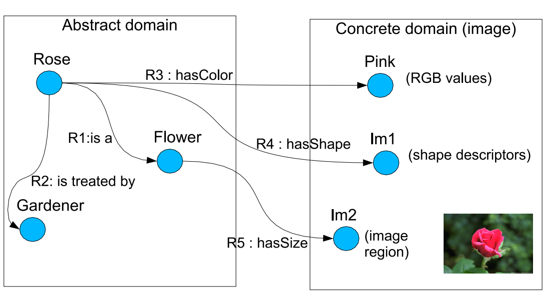


Fig. 2. Importance of concrete domains in image interpretation.

4. Importance of spatial relations

Spatial relations between objects of a scene or an image is of prime importance, as highlighted in different domains, such as perception, cognition, spatial reasoning, Geographic Information Systems, computer vision. In particular, the spatial arrangement of objects provides important information for recognition and interpretation tasks, in particular when the objects are embedded in a complex environment like in medical or remote sensing images [23,24]. Human beings use extensively spatial relations in order to describe, detect and recognize objects: they allow to solve ambiguity between objects having a similar appearance, and they are often more stable than characteristics of the objects themselves (this is typically the case of anatomical structures).

Many authors have stressed the importance of topological relations, but distances and directional relative position are also important, as well as more complex relations such as "between", "surround", "among", etc. Freeman [25] distinguishes the following primitive relations: left of, right of, above, below, behind, in front of, near, far, inside, outside, surround. Kuipers [24,26] considers topological relations (set relations, but also adjacency which was not considered by Freeman) and metrical relations (distances and directional relative position).

Spatial reasoning can be defined as the domain of spatial knowledge representation, in particular spatial relations between spatial entities, and of reasoning on these entities and relations (hence the importance of relations). This field has been largely developed in artificial intelligence, in particular using qualitative representations based on logical formalisms. In image interpretation and computer vision, it is much less developed and is mainly based on quantitative representations. In most domains, one has to be able to cope with qualitative knowledge, with imprecise and vague statements, with polysemy, etc. This calls for a common framework which is both general enough to cover large classes of problems and potential applications, and able to give raise to instantiations adapted to each particular application. Ontologies appear as an appropriate tool towards this aim. This shows the interest of associating ontologies and spatial relations for symbol grounding and image interpretation. Figure 3 illustrates a part of an ontology of spatial relations [27].

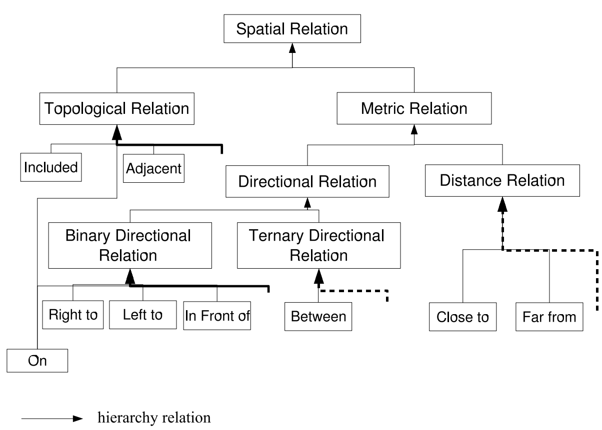


Fig. 3. Excerpt of the hierarchical organization of spatial relations in the ontology of [27].

As mentioned in [28], several ontological frameworks for describing space and spatial relations have been developed recently. In spatial cognition and linguistics, the project OntoSpace[f] aims at developing a cognitively-based commonsense ontology for space. Some interesting works on spatial ontologies can also be found in Geographic Information Science [29] or in medicine concerning the formalization of anatomical knowledge [30–32]. All these ontologies concentrate on the representation of spatial concepts according to the application domains. They do not provide an explicit and operational mathematical formalism for all the types of spatial concepts and spatial relations. For instance, in medicine, these ontologies are often restricted to concepts from the mereology theory [31]. They are therefore useful for qualitative and symbolic reasoning on topological relations but there is still a gap to fill before using them for image interpretation.

Example: internal brain structures are often described trough their spatial relations, such as: the ***left caudate nucleus*** *is* inside *the* ***left hemisphere****; it is* close *to the* ***lateral ventricle****; it is* outside (left of) *the* ***left lateral ventricle****; it is* above *the* ***thalamus****, etc. In case of pathologies, these relations are quite stable, but more flexibility should be allowed in their semantics [33].*

This example raises the problem of assigning semantics to these spatial relations, according to the application domain: what do concepts such as “close to” or “left” mean when dealing with brain images? Should this meaning be adapted depending on the context (possible pathology, etc.)? These questions can be addressed by using fuzzy models.

5. Importance of fuzzy representations

Usually vision and image processing make use of quantitative representations of spatial relations. In a purely quantitative framework, spatial relations are well defined for some classes of relations, unfortunately not for intrinsically vague relations (such as directional ones for instance). Moreover they need a precise knowledge of the objects and of the types of questions we want to answer. These two constraints can be relaxed in a semi-qualitative framework, using fuzzy sets. This allows to deal with imprecisely defined objects, with imprecise questions such as *are these two objects near to each other?*, and to provide evaluations that may be imprecise too, which is useful for several applications, where spatial reasoning under imprecision has to be considered. Note that this type of question also raises the question of polysemy, hence the need for semantics adapted to the domain. This is an important question to be solved in the symbol grounding and semantic gap problems.

Fuzzy set theory finds in spatial information processing a growing application domain. This may be

[f]http://www.ontospace.uni-bremen.de/twiki/bin/view/Main/WebHome

explained not only by its ability to model the inherent imprecision of such information (such as in image processing, vision, mobile robotics...) together with expert knowledge, but also by the large and powerful toolbox it offers for dealing with spatial information under imprecision. This is in particular highlighted when spatial structures or objects are directly represented by fuzzy sets. If even less information is available, we may have to reason about space in a purely qualitative way, and the symbolic setting is then more appropriate. In artificial intelligence, mainly symbolic representations are developed and several works addressed the question of qualitative spatial reasoning (see [34] for a survey). For instance in the context of mereotopology, powerful representation and reasoning tools have been developed, but are merely concerned by topological and part-whole relations, not by metric ones.

Limitations of purely qualitative spatial reasoning have already been stressed in [35], as well as the interest of adding semiquantitative extension to qualitative value (as done in the fuzzy set theory for linguistic variables [36,37]) for deriving useful and practical conclusions (as for recognition). Purely quantitative representations are limited in the case of imprecise statements, and of knowledge expressed in linguistic terms. As another advantage of fuzzy representations, both quantitative and qualitative knowledge can be integrated, using semi-quantitative (or semi-qualitative) interpretation of fuzzy sets. These representations can also cope with different levels of granularity of the information, from a purely symbolic level, to a very precise quantitative one. As already mentioned in [25], this allows us to provide a computational representation and interpretation of imprecise spatial constraints, expressed in a linguistic way, possibly including quantitative knowledge. Therefore the fuzzy set framework appears as a central one in this context. Several spatial relations have led to fuzzy modeling, as reviewed in [23].

Spatial reasoning aspects often imply the combination of various types of information, in particular different spatial relations. Again, the fuzzy set framework is appropriate since it offers a large variety of fusion operators [38,39] allowing for the combination of heterogeneous information (such as spatial relations with different semantics) according to different fusion rules, and without any assumption on an underlying metric on the information space. They also apply on various types of spatial knowledge representations (degree of satisfaction of a spatial relation, fuzzy representation of a spatial relation as a fuzzy interval, as a spatial fuzzy set, etc.). These operators can be classified according to their behavior, the possible control of this behavior according to the information to combine, their properties, and their specificities in terms of decision [40]. For instance, if an object has to satisfy, at the same time, several spatial constraints expressed as relations to other objects, the degrees of satisfaction of these constraints will be combined in a conjunctive manner, using a t-norm. If the constraints provide a disjunctive information, operators such as t-conorms are then appropriate. It is the case for example for symmetrical anatomical structures that can be found in the left or right parts of the human body. Operators with variable behavior, as some symmetrical sums, are interesting if the aim is a reinforcement of the dynamics between low degrees and high degrees of satisfaction of the constraints. In particular, this facilitates the decision since different situations will be better discriminated.

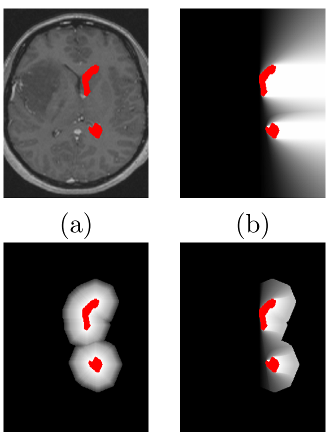
Let us come back to ontologies from the point of view of uncertain knowledge and imprecise information. A major weakness of usual ontological technologies is their inability to represent and to reason with uncertainty and imprecision. As a consequence, extending ontologies in order to cope with these aspects is a major challenge. This problem has been recently stressed out in the literature. Several approaches have been proposed to deal with uncertainty and imprecision in ontology engineering tasks [41,42]. The first approach is based on probabilistic extensions of the standard OWL ontology language[g] by using Bayesian networks [43,44]. The probabilistic approach proposes to first enhance the OWL language to allow additional probabilistic markups and then to convert the probabilistic OWL ontology into the directed acyclic graph of a Bayesian network with translation rules. As the main ontology language OWL is based on description logics [20], another approach to deal with uncertainty and imprecision is to use fuzzy description logics [45–48]. Fuzzy description logics can be classified according

[g] http://www.w3.org/TR/owl-features/

to the way fuzziness is introduced into the description logics formalism. A good review can be found in [49]. In particular, a common way for description logics with concrete domains is to introduce fuzziness by using fuzzy predicates in concrete domains as described in [50].

Another approach is to introduce fuzziness directly in the concrete domains, which then become fuzzy concrete domains. This is particularly interesting for image interpretation.

Example: Using fuzzy representations of spatial relations in the image domain leads to restricted search area for the ***caudate nucleus****, based on the knowledge that it is* <u>to the right</u> *and* <u>close</u> *to the* ***lateral ventricles****. This is illustrated in Figure 4.*



(a) (b) (c) (d)

Fig. 4. (a) The right ventricle is superimposed on one slide of the original image (MRI here). The search space of the object "caudate nucleus" corresponds to the conjunctive fusion of the spatial relations "**to the right of the right ventricle**" (b) and "**close to the right ventricle**" (c). The fusion result is shown in (d).

Example: Typically brain image interpretation may have to cope with abnormalities such as tumors. Our system allows instantiating generic knowledge expressed in the ontology to adapt to the specific patient's case. The fuzzy representations provide an efficient way to represent inter-individual variability, which are a key point in such situations. They can be further revised or specified according to the visual features extracted from the image and matched with the symbolic representation.

Using fuzzy representations, it is possible to deal with such cases, for instance by enlarging the areas where an object can be found, which amounts to relax the definition of the fuzzy relation.

In summary, fuzzy representations have several advantages:

- they allow representing the imprecision which is inherent to the definition of a concept; for instance, the concept "close to" is intrinsically vague and imprecise, and its semantics depends on the context in which objects are embedded, on the scale of the object and on their environment;
- they allow managing imprecision related to the expert knowledge in the concerned domain;
- they constitute an adequate framework for knowledge representation and reasoning, reducing the semantic gap between symbolic concepts and numerical information.

6. Towards the integration of ontologies, spatial relations and fuzzy models

To conclude this presentation, we summarize ongoing developments carried out in our team, towards the construction of a spatial relation ontology enhanced with fuzzy representations and its use for image interpretation. This work aims at integrating all important features underlined in this paper. A global scheme of our approach is provided in Figure 5.

Our recent work addresses the important problems highlighted in this paper in several ways [27,52]. We propose to reduce the semantic gap between numerical information contained in the image and higher level concepts by enriching ontologies with a fuzzy formalism layer. More specifically, we introduce an ontology of spatial relations and propose to enrich it by fuzzy representations of these relations in the spatial (image) domain. The choice of spatial relations is motivated on the one hand by the importance of structural information in image interpretation, and on the other hand by the intrinsically ambiguous nature of most spatial relations. This ontology has been linked to the part of FMA related to brain structures, as illustrated in Figure 5.

As another contribution, this enriched ontology can support the reasoning process in order to recognize structures in images, in particular in medical imaging. Different types of reasoning become then possible: (i) a quite general reasoning may consist in classifying or filtering ontological concepts to an-

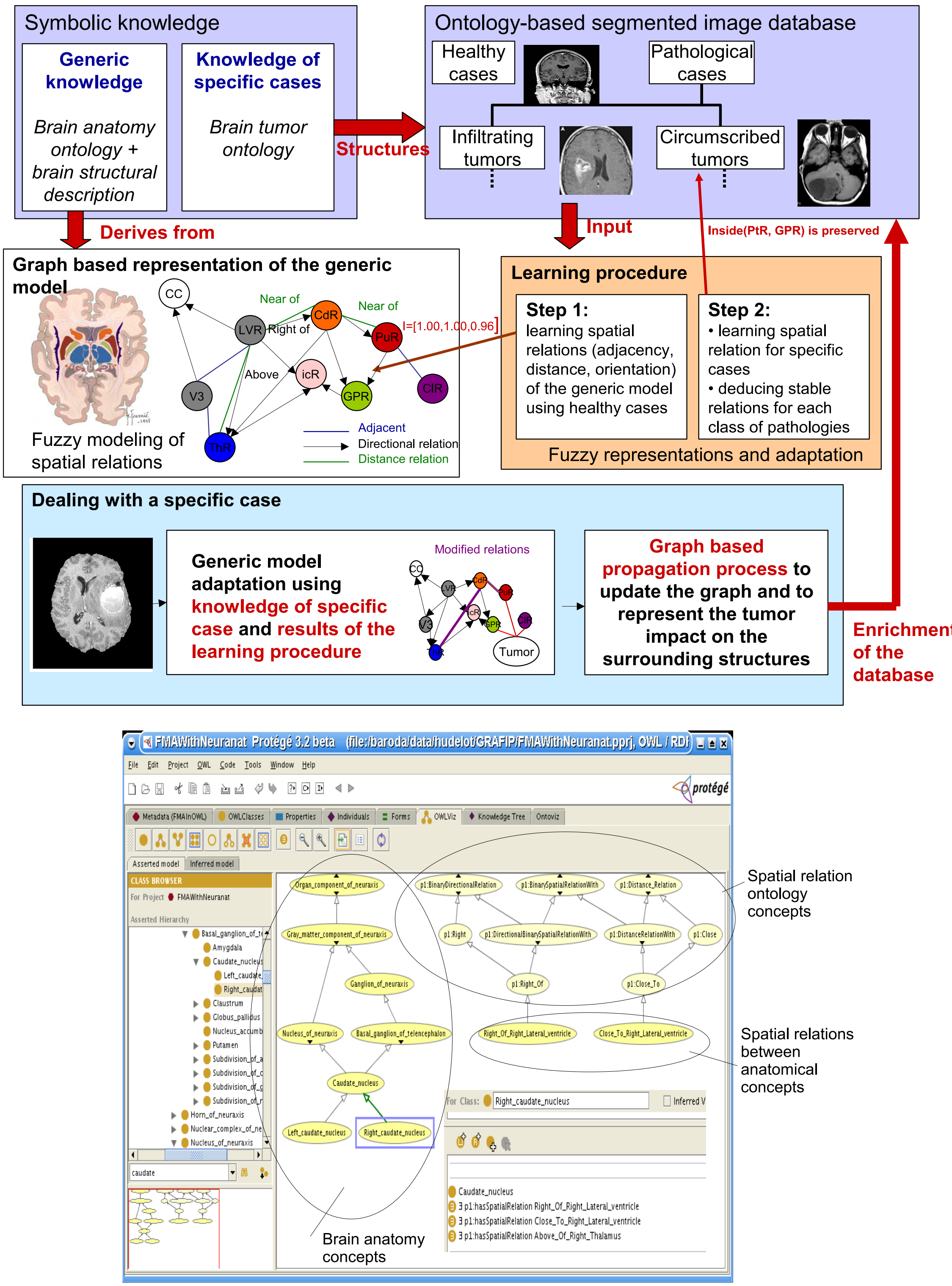


Fig. 5. Overview of our framework. Ontological engineering is used to represent the symbolic knowledge useful to interpret cerebral images. In particular, a spatial relation ontology is used to enrich the brain ontology by the description of the spatial structure of the brain. A graph based representation of the brain including learned fuzzy representations of spatial relations is derived from the generic model and from an image database. This graph is used to guide the segmentation and the recognition of cerebral structures. This framework is also useful to deal with pathological cases by an adaptation of the knowledge and the reasoning process. The second scheme displays a part of an ontology of brain anatomy (excerpt of the FMA [51]) enhanced with our fuzzy spatial relations ontology. The concepts of the spatial relation ontology are prefixed by **p1**.

swer some queries; (ii) at a more operational way, the ontology and the fuzzy representations can be used to deduce spatial reasoning operations in the images and to guide image interpretation tasks such as localization of objects, segmentation, and recognition. An illustration is provided in Figure 6 for the recognition of internal brain structures.

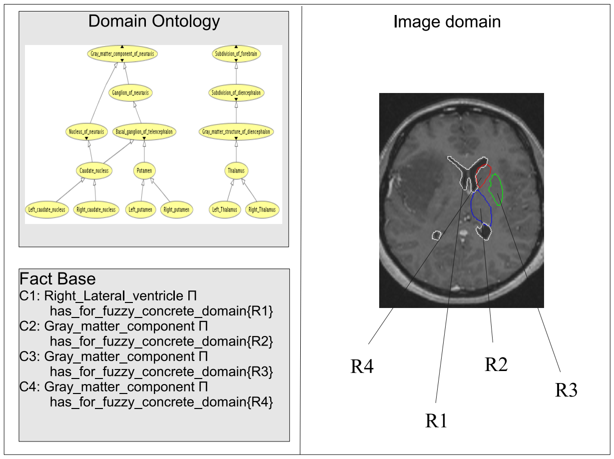


Fig. 6. The right lateral ventricle corresponds to the spatial region R1 in the image. The domain ontology describes spatial relations between several grey nuclei and the lateral ventricles. These relations are exploited to identify each individual structure.

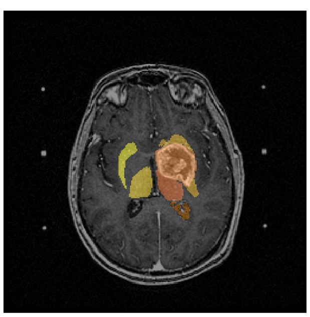


Fig. 7. An axial slice of a 3D MRI, with segmented tumor and some anatomical structures.

Another enrichment of the model consists of the representation of domain knowledge by graphs, which include fuzzy models of spatial relations, used to guide the recognition of individual structures in images [53]. The inclusion of such structural models, as intermediate representation domains between symbols and images, deals with the physical symbol grounding problem, and also contributes to reduce the semantic gap. However pathological cases may deviate substantially from generic knowledge. We propose to adapt the knowledge representation to take into account the possible influence of pathologies on the spatial organization, based on learning procedures. We also adapt the reasoning process, based on graph based propagation and updating. These features of our approach are detailed in [52]. A result is illustrated in Figure 7.

The enriched ontology contributes to reduce the semantic gap and to answer some symbol grounding questions, which are difficult and still open problems in image interpretation. It provides tools both for knowledge acquisition and representation and for its operational use. It has an important potential in model-based recognition that deserves to be further explored, in particular for medical image interpretation. The framework described in this section focuses on spatial relations, but similar principles can be applied to other types of information that could be involved in image interpretation.

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References

1. S. Harnad, *Physica* **42**, 335 (1990).
2. J. Searle, *Behavioral and Brain Sciences* **3**, 417 (1980).
3. M. Taddeo and L. Floridi, *Journal of Experimental and Theorical Artificial Intelligence* (2006).
4. S. Coradeschi and A. Saffiotti, *Robotics and Autonomous Systems* **43**, 85 (2003), Special issue on perceptual anchoring. Online at http://www.aass.oru.se/Agora/RAS02/.
5. I. Bloch and A. Saffiotti, Some similarities between anchoring and pattern recognition concepts, in *AAAI Fall Symposium on Anchoring Symbols to Sensor Data in Single and Multiple Robots Systems*, 2001.
6. A. Smeulders, M. Worring, S. Santini, A. Gupta and R. Jain, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **22**, 1349 (2000).
7. D. Roy, *Computer Speech and Language* **16** (2002).
8. P. Vogt, *Artificial Intelligence* **167**, 206 (2005).
9. A. Cangelosi, *Pragmatics and Cognition, Special Issue on Distributed Cognition* (2006), in press.
10. T. R. Gruber, Towards Principles for the Design of Ontologies Used for Knowledge Sharing, in *For-*

mal Ontology in Conceptual Analysis and Knowledge Representation, eds. N. Guarino and R. Poli (Kluwer Academic Publishers, Deventer, The Netherlands, 1993).

11. P. Zweigenbaum, B. Bachimont, J. Bouaud, J. Charlet and J. Boisvieux, *Meth Inform Med* **34**, p. 2 (1995).
12. A. Jakulin and D. Mladenic, Ontology grounding, in *Conference on Data Mining and Data Warehouses*, (Ljubljana, Slovenia, 2005).
13. C. Town, *Machine Vision and Applications* (2006).
14. A. Schreiber, B. D. ans J. Wielemaker and B. Wielinga, *IEEE Intelligent Systems* **16**, 66 (2001).
15. B. Hu, S. Dasmahapatra, P. Lewis and N. Shadbolt, Ontology-based medical image annotation with description logics, in *15th IEEE International Conference on Tools with Artificial Intelligence*, 2003.
16. C. Hudelot, N. Maillot and M. Thonnat, Symbol grounding for semantic image interpretation: from image data to semantics, in *Proceedings of the Workshop on Semantic Knowledge in Computer Vision, ICCV*, (Beijing, China, 2005).
17. W. Z. Mao and D. A. Bell, Integrating visual ontologies and wavelets for image content retrieval, in *DEXA Workshop*, 1998.
18. V. Mezaris, I. Kompatsiaris and M. G. Strintzis, *Eurasip Journal on Applied Signal Processing* **2004**, 886 (2004).
19. G. Guerra-Filho and Y. Aloimonos, Towards a sensorimotor wordnet: Closing the semantic gap, in *Proceedings of the Third International Wordnet Conference*, january 2006.
20. F. Baader, D. Calvanese, D. McGuinness, D. Nardi and P. Patel-Schneider, *The Description Logic Handbook: Theory, Implementation and Applications* (Cambridge University Press, 2003).
21. M. Aufaure and H. Hajji, *Multimedia Information Systems* , 38 (2002).
22. K. Petridis, D. Anastasopoulos, C. Saathoff, N. Timmermann, I. Kompatsiaris and S. Staab, *Engineered Applications of Semantic Web Session (SWEA) at the 10th International Conference on Knowledge-Based & Intelligent Information & Engineering Systems (KES 2006)* (2006).
23. I. Bloch, *Image and Vision Computing* **23**, 89 (2005).
24. B. J. Kuipers and T. S. Levitt, *AI Magazine* **9**, 25 (1988).
25. J. Freeman, *Computer Graphics and Image Processing* **4**, 156 (1975).
26. B. Kuipers, *Cognitive Science* **2**, 129 (1978).
27. C. Hudelot, J. Atif and I. Bloch, Ontologie de relations spatiales floues pour l'interprétation d'images, in *Rencontres francophones sur la Logique Floue et ses Applications, LFA 2006*, (Toulouse, France, 2006).
28. J. Bateman and S. Farrar, Towards a generic foundation for spatial ontology, in *International Conference on Formal Ontology in Information Systems (FOIS-2004)*, (Trento, Italy, 2004).
29. R. Casati, B. Smith and A. Varzi, Ontological Tools for Geographic Representation, in *Formal Ontology in Information Systems*, ed. N. Guarino (IOS Press, Amsterdam, 1998) pp. 77–85.
30. O. Dameron, Symbolic model of spatial relations in the human brain, in *Mapping the Human Body: Spatial Reasoning at the Interface between Human Anatomy and Geographic Information Science*, (University of Buffalo, USA, 2005).
31. M. Donnelly, T. Bittner and C. Rosse, *Artificial Intelligence in Medicine* **36**, 1(January 2006).
32. S. Schulz, U. Hahn and M. Romacker, Modeling anatomical spatial relations with description logics, in *Annual Symposium of the American Medical Informatics Association. Converging Information, Technology, and Health Care (AMIA 2000)*, (Los Angeles, CA, 2000).
33. J. Atif, H. Khotanlou, E. Angelini, H. Duffau and I. Bloch, Segmentation of Internal Brain Structures in the Presence of a Tumor, in *MICCAI*, (Copenhagen, 2006).
34. L. Vieu, Spatial Representation and Reasoning in Artificial Intelligence, in *Spatial and Temporal Reasoning*, ed. O. Stock (Kluwer, 1997) pp. 5–41.
35. S. Dutta, *International Journal of Approximate Reasoning* **5**, 307 (1991).
36. L. A. Zadeh, *Information Sciences* **8**, 199 (1975).
37. D. Dubois and H. Prade, *Fuzzy Sets and Systems: Theory and Applications* (Academic Press, New-York, 1980).
38. D. Dubois and H. Prade, *Information Sciences* **36**, 85 (1985).
39. D. Dubois, H. Prade and R. Yager, Merging Fuzzy Information, in *Handbook of Fuzzy Sets Series, Approximate Reasoning and Information Systems*, eds. J. Bezdek, D. Dubois and H. Prade (Kluwer, 1999)
40. I. Bloch, *IEEE Transactions on Systems, Man, and Cybernetics* **26**, 52 (1996).
41. P. da Costa et al. (Eds), *Proceedings of the ISWC Workshop on Uncertainty Reasoning for the Semantic Web*, 2005).
42. E. Sanchez (ed.), *Fuzzy Logic and the Semantic Web* (Elsevier, 2006).
43. Z. Ding, Y. Peng and R. Pan, A Bayesian Approach to Uncertainty Modelling in OWL Ontology, in *International Conference on Advances in Intelligent Systems-Theory and Applications (AISTA2004)*, (Luxembourg-Kirchberg, Luxembourg, 2004).
44. Y. Yang and J. Calmet, Ontobayes: An ontology-driven uncertainty model, in *International Conference on Intelligent Agents, Web Technology and Internet Commerce (IAWTIC'05)*, 2005.
45. S. Holldobler, T. Khang and H. Storr, *Proceedings InTech/VJFuzzy* **2002**, 25 (2002).
46. Y. Li, B. Xu, J. Lu, D. Kang and P. Wang, A family of extended fuzzy description logics, in *29th Annual International Computer Software and Applications*

Conference (COMPSAC'05), (IEEE Computer Society, Los Alamitos, CA, USA, 2005).

47. G. Stoilos, G. Stamou and J. Pan, Handling imprecise knowledge with fuzzy description logic, in *International Workshop on Description Logics (DL 06)*, (Lake District, UK, 2006).
48. U. Straccia, Description logics with fuzzy concrete domains, in *21st Conference on Uncertainty in Artificial Intelligence (UAI-05)*, eds. F. Bachus and T. Jaakkola (AUAI Press, Edinburgh, Scotland, 2005).
49. M. d'Aquin, J. Lieber and A. Napoli, Etude de quelques logiques de description floues et de formalismes apparentés, in *Rencontres Francophones sur la Logique Floue et ses Applications*, (Nantes, France, 2004).
50. U. Straccia, A fuzzy description logic for the semantic web, in *Fuzzy Logic and the Semantic Web*, ed. E. Sanchez (Elsevier, 2006) pp. 73–90.
51. C. Rosse and J. L. V. Mejino, *Journal of Biomedical Informatics* **36**, 478 (2003).
52. J. Atif, C. Hudelot, I. Bloch and E. Angelini, From Generic Knowledge to Specific Reasoning for Medical Image Interpretation using Graph-based Representations, in *International Joint Conference on Artificial Intelligence IJCAI'07*, (Hyderabad, India, 2007).
53. O. Colliot, O. Camara and I. Bloch, *Pattern Recognition* **39**, 1401 (2006).