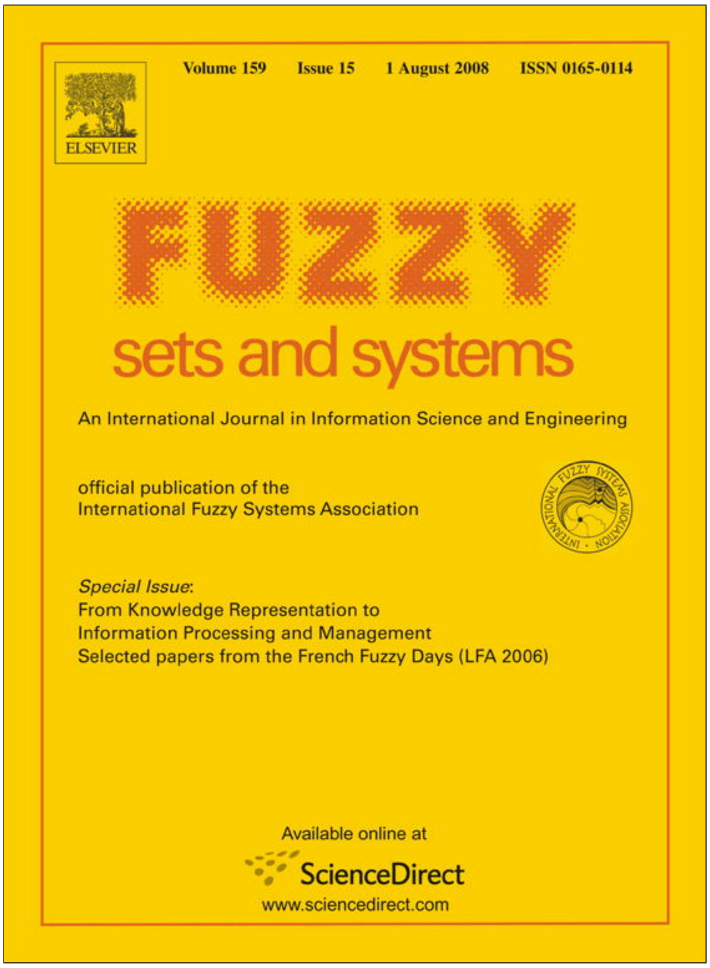
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Fuzzy spatial relation ontology for image interpretation

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Abstract

The semantic interpretation of images can benefit from representations of useful concepts and the links between them as ontologies. In this paper, we propose an ontology of spatial relations, in order to guide image interpretation and the recognition of the structures it contains using structural information on the spatial arrangement of these structures. As an original theoretical contribution, this ontology is then enriched by fuzzy representations of concepts, which define their semantics, and allow establishing the link between these concepts (which are often expressed in linguistic terms) and the information that can be extracted from images. This contributes to reducing the semantic gap and it constitutes a new methodological approach to guide semantic image interpretation. This methodological approach is illustrated on a medical example, dealing with knowledge-based recognition of brain structures in 3D magnetic resonance images using the proposed fuzzy spatial relation ontology.

Keywords: Fuzzy representations; Ontology; Spatial relations; Image interpretation; Semantic gap

1. Introduction

The importance of semantics in images has been highlighted in different domains such as scene analysis, image interpretation, and content-based indexing of digital images. 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. Introducing knowledge in the image interpretation process is not a new idea, as evidenced by the numerous work on knowledge-based systems for computer vision (see for instance a review in [20] or more recent works in [17,71]). However, this type of approach suffers from several shortcomings, in particular because of the lack of genericity (many systems are rather ad hoc), and the difficulty of acquiring and representing prior knowledge. Recent developments in the field of knowledge engineering, including ontology engineering, allow answering some of these questions [43]. The use of ontologies is also widening in the domain of image indexation [72]. However, the development of ontology-based methods for image interpretation is still in its infancy.

As opposed to the domain of analysis and indexation of textual documents, in which ontologies are widely used and became an almost unavoidable support, the domain of image interpretation and semantic indexing has to face the difficult problem of matching the perceptual level and the conceptual level. The perceptual level consists of features,

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mainly pixels (in 2D), voxels (in 3D), or groups of pixels or voxels, while the concepts are usually expressed in plain text and have a linguistic nature. This problem is often referred to as the semantic gap, defined as "the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation'' [64]. It is close to the problem of symbol grounding or anchoring addressed in artificial intelligence [39] and in robotics [19].

An important type of knowledge that guides spatial reasoning (and therefore image interpretation) consists of spatial relations, as advocated by works in many domains, such as philosophy, linguistics, perception, cognition, robotics, artificial intelligence, geographic information systems (GIS), or computer vision. Our research focuses on image interpretation based on prior knowledge on the spatial organization of the observed structures.

Alternative approaches such as Markov random fields (MRFs) and probabilistic relaxation, described in [47], enable to introduce and model the spatial context to guide image interpretation. Nevertheless, in these approaches, the formal models and the contextual information are both different from the ones in our proposal. Recently, our work on spatial relations has been used by another group in a MRF framework [61], but usually the context is considered in a much more local way and does not model the whole scene.

In this paper, 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. 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 objects and of 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.

More specifically, we introduce an ontology of spatial relations and propose to enrich it by fuzzy representations of these relations in the spatial 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.

As another contribution of this paper, we show how this enriched ontology can support the reasoning process in order to recognize structures in images. Examples are taken from the field of medical imaging, and allow illustrating the proposed approach with concrete situations.

Once linked to an anatomy ontology, our enriched ontology exhibits all required characteristics for ontologies in the domain of biomedicine, according to [14]: good lexical coverage, good coverage in terms of relations, compatibility with standards, modularity, and ability to represent variation in reality. This is achieved in particular by the separation between the different levels and the fuzzy layer we propose.

The paper is organized as follows. In Section 2, we underline the importance of spatial relations for image understanding. We also briefly recall the definition of an ontology and review the literature on the introduction of uncertainty and imprecision in ontologies. We propose in Section 3 an ontology of spatial relations and we briefly present fuzzy models of spatial relations. In Section 4, we describe the formal representation of the proposed ontology and we detail the integration between the ontology and the fuzzy models with concrete domains. In Section 5, we propose a methodological approach using the proposed fuzzy spatial relation ontology to perform structural pattern recognition in the context of semantic image interpretation. As an illustrative example, brain structure recognition is presented. It illustrates the potential of the proposed fuzzy spatial relation ontology.

2. Related work

2.1. Importance of spatial relations

Spatial relations between objects of a scene or image is of prime importance, as mentioned in Section 1. 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 [9,49]. Human beings make extensive use of 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, as illustrated in Section 5). 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 [33] distinguishes the following primitive relations: left of, right of, above, below, behind, in front of, near, far, inside, outside, and surround. Kuipers [48,49] considers topological relations (set relations, but also adjacency which was not considered by Freeman) and metrical relations (distances and directional relative position). The framework proposed in this paper takes all these relations into account and is open to any more complex ones.

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 [73]. In image interpretation and computer vision, it is much less developed and is mainly based on quantitative representations. In most domains, one has 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 rise to instantiations adapted to each particular application. Ontologies appear as an appropriate tool toward this aim.

2.2. Dealing with uncertainty and imprecision in ontology

In knowledge engineering, an ontology is defined as *a formal*, *explicit specification of a shared conceptualization* [35]. 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 [76]. However, most real world domains contain uncertain knowledge and imprecise and vague 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 in the literature, and several approaches have been proposed to deal with uncertainty and imprecision in ontology engineering tasks [21,60]. The first approach is based on probabilistic extensions of the standard OWL ontology language [3] by using Bayesian networks [27,75]. The probabilistic approach proposes to first augment 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 (DL) [3], another approach to deal with uncertainty and imprecision is to use fuzzy DL [42,51,67,68]. Fuzzy DL can be classified according to the way fuzziness is introduced into the DL formalism. A good review can be found in [24]. In particular, a common approach is to introduce fuzziness by using fuzzy predicates in concrete domains as described in [69].

DL [3] are a family of knowledge-based representation systems mainly characterized by *a set of constructors* that enable to build complex *concepts* and *roles* from atomic ones. Due to their well-defined semantics and to their powerful reasoning tools, DL are perfect candidates for ontology languages as explained in [3]. In DL, a semantics is associated with concepts, roles and individuals 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 DL.

Concrete domains are expressive means of DL that enable to describe concrete properties of real world objects such as their size, their spatial extension or their color. For instance, in the DL formalism given in Table 1, the concept Person $\sqcap \exists age.\leqslant_{20}$ denotes the set of persons whose age is lower than or equal to 20. In this example $\leqslant_{20}$ is a predicate over the concrete domain of natural numbers $\mathbb{N}$. As a consequence, a fuzzy extension can be obtained with fuzzy sets defined on the concrete domains. For instance to denote the concept YoungPerson as YoungPerson $\equiv$ Person $\sqcap\exists$ age.Young, we can define the fuzzy concrete predicate over the natural numbers Young: $\mathbb{N} \rightarrow [0, 1]$ which represents the degree of youngness of a person according to usual modeling methods in fuzzy set theory [30]. Young can be represented by a trapezoidal membership function for instance. In fuzzy DL, *concepts* and *roles* are interpreted as fuzzy subsets of an

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

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	$\bot$	Nothing	$\bot^{\mathcal{I}} = \emptyset^{\mathcal{I}}$
Atomic role	r	has-age	$R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$
Conjunction	$C \sqcap D$	Human ⊓ Male	$C^{\mathcal{I}} \cap D^{\mathcal{I}}$
Disjunction	$C \sqcup D$	Male ⊔ Female	$C^{\mathcal{I}} \cup D^{\mathcal{I}}$
Negation	$\neg C$	¬ Human	$\Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$
Existential restriction	$\exists r.C$	∃ 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	$\forall r.C$	∀ 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	$\ni r.\{a\}$	∋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	$(\geqslant n R)$	(⩾3 has-child)	$\{x \in \Delta^{\mathcal{I}} \mid \ \lvert\{y \mid (x, y) \in R^{\mathcal{I}}\}\rvert \geqslant n\}$
	$(\leqslant n R)$	(⩽1 has-mother)	$\{x \in \Delta^{\mathcal{I}} \mid \ \lvert\{y \mid (x, y) \in R^{\mathcal{I}}\}\rvert \leqslant n\}$
Subsumption	$C \sqsubseteq D$	Man ⊑ Human	$C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$
Concept definition	$C \equiv D$	Father ≡ Man ⊓ ∃ 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	$(a^{\mathcal{I}}, b^{\mathcal{I}}) \in R^{\mathcal{I}}$

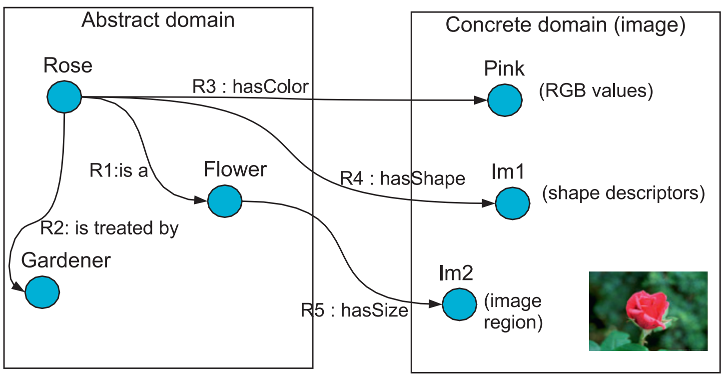


Fig. 1. Importance of concrete domains in image interpretation.

interpretation domain, and axioms, rather than being satisfied (true) or unsatisfied (false) in an interpretation, become a degree of truth in [0, 1]. More details about the semantics of fuzzy DL can be found in [69].

As illustrated in the previous example, concrete domains can be natural, real, or rational numbers but they can also be more structured datatypes. For instance, in [36], a concrete domain *Polygon* is used to represent the spatial dimension and to combine spatial knowledge representation (restricted to topology in this work) and spatial reasoning in a unique paradigm. In image interpretation, we can consider the image domain as a concrete domain. For instance as illustrated in Fig. 1, *Pink* can be considered as a predicate over the concrete domain of RGB values. As a consequence, these predicates defined over concrete domains can be a means of reducing the semantic gap.

In this paper, we are only interested in the representation of spatial relations which enable to represent structural knowledge by opposition to image features such as color or texture. Their ability to describe scenes and to disambiguate object recognition makes them useful for a wide range of imaging applications including aerial image interpretation [44,53], face recognition [16], and medical imaging [18,63]. As a consequence, image interpretation should greatly benefit from a generic ontology of spatial relations.

3. An ontology of spatial relations

As mentioned in [4], several ontological frameworks for describing space and spatial relations have been developed recently. In spatial cognition and linguistics, the project OntoSpace [4] aims at developing a cognitively based commonsense ontology for space. Some interesting works on spatial ontologies can also be found in GIS [15,46], in object recognition in images or videos [26,38], in robotics [28], or in medicine concerning the formalization of anatomical knowledge [22,23,29,62]. 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 [29]. These concepts are fundamental for spatial relations ontologies [66], and these ontologies are useful for qualitative and symbolic reasoning on topological relations, but there is still a gap to fill before using them for image interpretation.

Moreover, to our knowledge, none of these ontologies take into account the vagueness and the subjectivity of spatial information, even if many frameworks for spatial knowledge representation and spatial reasoning under imprecision have been proposed. An interesting work dedicated to the representation of uncertain, subjective and vague temporal knowledge in ontologies has been proposed in [56]. A fuzzy temporal model is integrated into an ontology by using fuzzy predicates over concrete domains (fuzzy intervals). We propose to develop similar ideas for the representation of spatial knowledge. In particular, we propose a generic spatial ontology enriched with fuzzy representations of spatial concepts in the image domain. This modular representation enables to keep abstract generic spatial concepts separated from their application dependent representation. Moreover, it provides a unified framework for the representation of spatial information in images and it makes image processing and interpretation easier.

In this section, we describe the main concepts which have been highlighted in the literature for their importance for spatial reasoning, and which are therefore integrated in our ontology. An excerpt of the hierarchical organization of spatial relations in our ontology is displayed in Fig. 2. Moreover, details on fuzzy representations of spatial relations are given for each type of spatial relations.

3.1. Fuzzy representations of spatial relations: some preliminaries

Representation of objects by spatial fuzzy sets: A spatial fuzzy set is a fuzzy set defined on the image space, denoted by $\mathcal{S}$, $\mathcal{S}$ being typically $\mathbb{Z}^2$ or $\mathbb{Z}^3$ for 2D or 3D images. Its membership function μ (defined from $\mathcal{S}$ into $[0, 1]$) represents the imprecision on the spatial definition of the object (its position, size, shape, boundaries, etc.). For each point x of $\mathcal{S}$ (pixel or voxel in digital 2D or 3D images), $\mu(x)$ represents the degree to which x belongs to the fuzzy object. Objects defined as classical crisp sets are particular cases, for which μ takes only values 0 and 1. In the following, all definitions will include the crisp case as a particular case, so that the complete framework applies for both crisp and fuzzy objects and relations.

The complement of an object defined by its membership function μ is classically defined by the membership function $c(\mu)$ where c is a fuzzy complementation (typically $c(a) = 1 - a$).

Types of representations: Different approaches can be chosen to model spatial relations by fuzzy sets and as a consequence, the fuzzy representations of spatial relations can be of various natures: fuzzy number, spatial fuzzy set, interval, angle histogram, etc. The choice of the representation depends on the relation but also on the type of question raised and the type of reasoning one wants to perform. Typically, in spatial reasoning, questions and reasoning may concern:

(1) The relations that are satisfied or not between two given objects (or satisfied to some degree) (Fig. 3);
(2) The region of the space $\mathcal{S}$ where a relation to one reference object is satisfied (to some degree) (Fig. 4).

While in the crisp case, a relation between two objects is usually represented by a number (either 0/1 for an all-or-nothing relation, or a numerical value for a distance for instance), in the fuzzy case, several representations are possible. They can typically be intervals, for instance representing necessity and possibility degrees, fuzzy numbers, distributions. Details can be found in [8] in the case of distances. These representations are adequate to answer questions of type 1, since they rely on some computation procedure between two known objects. As for the second type of question,

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

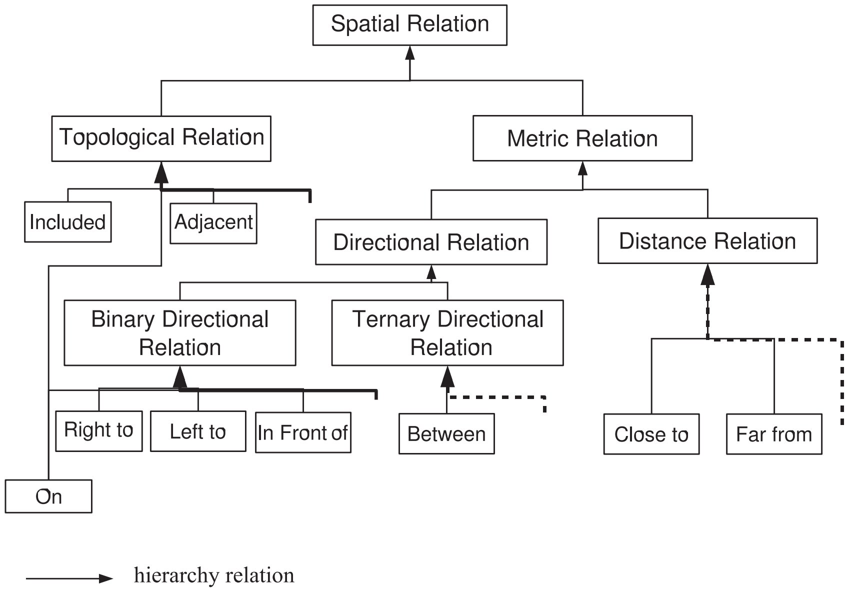


Fig. 2. Excerpt of the hierarchical organization of spatial relations in our ontology.

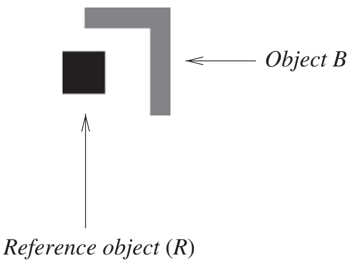


Fig. 3. Illustration of the first type of question: Given two objects R and B, what are the relations between them? For instance, is object B close to reference object R? Is it to the right of R?

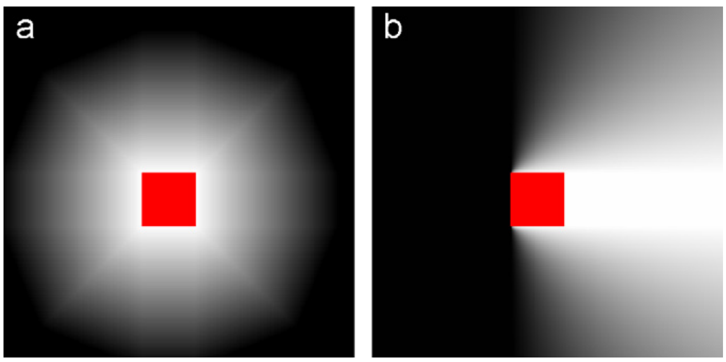


Fig. 4. Illustration of the second type of question: given a reference object R (the square), what are the regions of space that satisfy a relation to it? (a) Region of space close to R, represented as a spatial fuzzy set where the membership degree at each point represents the degree to which the relation is satisfied at this point (white = 1, black = 0). (b) Region of space to the right of R.

spatial representations are more appropriate, as fuzzy sets in the spatial domain (see the examples in Fig. 4). In these representations, the membership value at each point represents the degree to which the relation is satisfied.

In terms of concrete domains, for the first type of representations and of question to be answered, the fuzzy sets are defined over concrete domains which are typically the real line. On the contrary for the second type of representations, the concrete domain is the image support (spatial domain).

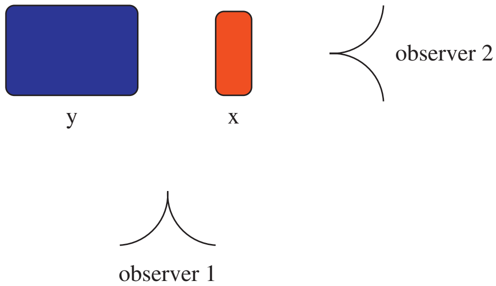


Fig. 5. Influence of the reference system: **x** is to the right of **y** for observer 1 but not for observer 2.

Let us now detail some spatial relations and their fuzzy definitions we rely on (see e.g. [9] for a synthesis of the existing fuzzy definitions of spatial relations).

3.2. Reference system

Making spatial relations explicit, in particular metric relations, requires a reference system. Let us consider the example of the directional relation "**x** *in front of* **y**''. The semantics of the relation is not the same depending on whether the reference system is object **y** itself or an external observer. In order to define a binary relation between two objects, at least the three following concepts have to be specified: the target object, the reference object, and the reference system. Works in spatial cognition have intensively addressed this question [45]. In general, a reference system is categorized either from the observer's point of view (which can be relative or absolute), or according to the way the relation is used (intrinsic, extrinsic, or deictic use). It is therefore important to integrate the notion of reference system in the ontology. In the proposed spatial relation ontology, each metrical relation (directional relation or distance) is linked explicitly to a given reference system and the use of the relation requires defining the reference system associated to the relation. Fig. 5 illustrates the importance of the reference system: the relation between the two objects differs depending on the observer.

3.3. A few types of spatial relations

3.3.1. Topological relations

Topology is a fundamental aspect of space. Binary topological relations between two objects are based on notions of intersection, interior, and exterior. The literature is quite abundant on the formalization of topological relations (see e.g. [73] for a review of the qualitative formalisms). One of the main approaches is the Region Connection Calculus (RCC) theory [57], in which relations between closed and connected spatial entities are derived from a connection predicate. In this theory, eight main exclusive relations are defined. It was extended to imprecise objects via the egg-yolk approach [40]. Another approach, known as nine-intersections [34], uses a partition of space into three regions for each object (its boundary, its interior and its complement), which constitutes the basis for computing relations. One of the advantages of these approaches is that they build an exhaustive set of topological relations from the basic ones. They are organized in a lattice and are involved in logical reasoning tools. Expressing *in extenso* all relations of interest is unfortunately not possible for other types of relations, for which many different types of specifications usually exist.

Besides these qualitative formalisms, quantitative approaches allow expressing all these relations for digital objects using values: 0/1 for relations expressed in an all-or-nothing manner, numbers or fuzzy numbers for expressing degrees to which relations hold (degree of adjacency, degree of overlap, etc.).

Fuzzy representations of topological relations: Relations such as "intersects'' (connection relation of the mereotopology), "in the interior of'' (inclusion), and "exterior to'' (exclusion) can be simply defined from fuzzy set theoretical concepts (complementations c, t-norms t, t-conorms T [30]). The two types of questions can be easily addressed for inclusion and exclusion, and it is possible to define the degree to which a fuzzy object ν is included in another one μ, for instance by

$$\inf_{x \in \mathcal{S}} T(c(\nu(x)), \mu(x)),$$

as well as the degree to which a point x is in the interior of a fuzzy set μ, for instance simply by $\mu(x)$.

Adjacency between two fuzzy sets can be defined from a non-symmetrical visibility concept [58], or in a symmetrical way from topological concepts [12]. In both cases, mainly the first type of question can be addressed.

Besides these simple topological spatial relations, the ontology also contains the RCC mereotopological relations which are organized according to the subsumption hierarchy proposed in [57]. It should be noted that our framework, dedicated to fuzzy representations of spatial relations, can also cope with non fuzzy ones (such as the RCC relations for instance).

3.3.2. Directional relations

Directional relations, which are useful to describe the relative position of an object with respect to other ones, require the space to be oriented, i.e. a reference system, as described below. The most used relations are related to three axes of references: "To the right of'', "To the left of'', "Above'', "Below'', "In front of'', "Behind''. More specific relations can be derived by combining some of these basic ones, such as "In front and left of''. Although these main directions are the most usual ones, nothing prevents from using a finer granularity on the set of directions.

More complex relations in this category include for instance the ternary relation "Between'' or the binary relation "Along''. The natural language has many terms for speaking about such relations, which are sometimes very difficult to model mathematically [41,70]. Fuzzy representations of these relations have been proposed, taking into account a few typical situations [10]. As opposed to topological relations, it would be very difficult to define exhaustively a set of relations with a large enough degree of genericity. The same remarks hold for distances. However, our framework is open and allows for an easy inclusion of new relations of interest.

Fuzzy representations of directional relations: This type of relation is ambiguous and imprecise even if objects are crisp. Therefore, relative position concepts are typical examples where they may find a better understanding in the framework of fuzzy sets, as fuzzy relations, even for crisp objects. This framework makes it possible to propose flexible definitions which fit the intuition and may include subjective aspects, depending on the application and on the requirements of the user. Several definitions have been proposed by a few teams, and a synthesis can be found in [13]. They differ through the representation they use for objects and relations. Objects can be represented by one point only, by their projection on one axis, or by complete spatial fuzzy sets. Relations can be defined by numbers, fuzzy numbers, intervals, angle histograms, or their extensions as histograms of forces. These histograms represent all relative directions between the objects [52,54]. In this case, the answer to the first question for a given relation requires to extract the information specific to this relation from the histogram, for instance by comparison with a fuzzy subset of the set of angles representing the semantics of the relation. Histogram representations also allow determining the dominant relation between two objects.

As for the second type of question, a spatial representation has been proposed in [7]. We consider a reference object R and a directional relation to be evaluated. A fuzzy "landscape'' is defined around the reference object R as a fuzzy set such that the membership value of each point corresponds to the degree of satisfaction of the considered spatial relation. This is formally defined by a fuzzy dilation of R by a fuzzy structuring element representing the desired relation with respect to the origin. Details about the formalization and the properties, as well as some algorithmical and computational aspects, can be found in [7]. Note that this approach can be followed by a second step in order to answer the first type of question, by evaluating how well the second object matches with the areas having high membership values (i.e. areas that are in the desired direction), using for instance a fuzzy pattern matching approach.

Histogram and fuzzy landscape approaches are illustrated in Fig. 6.

Currently, the ontology contains the six main directional relations, i.e. "To the right of'', "To the left of'', "Above'', "Below'', "In front of'', and "Behind''. The reference system is given by the coordinate frame of the spatial domain. The conjunction, disjunction, and negation constructors of the DL can be used to specialize these different directional relations. Moreover, the ontology contains the following cardinal directional relations: "To the north of'', "To the south of'', "To the West of'', and "To the East of''.

3.3.3. Distances

Distances are also very commonly used to describe the spatial arrangement of objects. A distance relation can be represented by a number of $\mathbb{R}^+$ ("At a distance of''). It can also be specialized under less precise forms, using relations such as "Close to'' and "Far from''. The degree of granularity can be further modified using quantifiers (for instance "Very far from'').

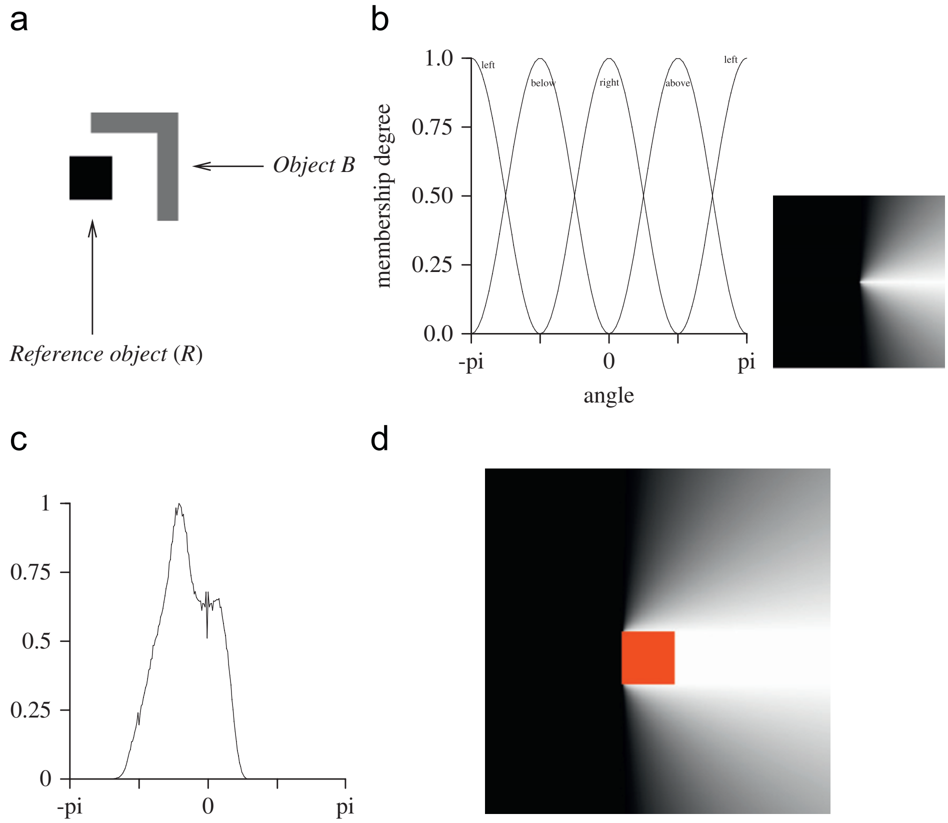


Fig. 6. (a) Two objects. (b) Semantics of directional relations for four main directions, represented as fuzzy sets on the angle space (left), and fuzzy structuring element ν representing the semantics of "to the right of'' in the spatial domain (right). (c) Angle histogram between the two objects, showing the dominance of the relation "to the right of''. (d) Fuzzy dilation of object R (the square) by the fuzzy structuring element ν.

Fuzzy representations of distance relations: Several definitions can be found in the literature for distances between fuzzy sets (which is the main addressed problem). They can be roughly divided into two classes: distances that take only membership functions into account and that compare them point-wise, and distances that additionally include spatial distances (see e.g. [8] for a review). The definitions which combine spatial distance and fuzzy membership comparison allow for a more general analysis of structures in images, for applications where the topological and spatial arrangement of the structures of interest is important (segmentation, classification, and scene interpretation). These distances combine membership values at different points in the space $\mathcal{S}$, and take into account their proximity or distance in $\mathcal{S}$. The price to pay is an increased complexity, generally quadratic in the cardinality of $\mathcal{S}$. In [8] original approaches were proposed for defining fuzzy distances taking into account spatial information, which are based on fuzzy mathematical morphology, exploiting the strong links existing between mathematical morphology (in particular dilation) and distances (from a point to a set, and between two sets). The advantage is that distances are expressed algebraically, in set theoretical terms, and are therefore easier to translate to the fuzzy case with nice properties than usual analytical expressions. All these approaches are adequate to address the first type of question.

Let us now consider the second question, i.e. defining the area of the space that satisfies some distance property with respect to a reference object. We assume that a set A is known as one already recognized object, or a known area of $\mathcal{S}$, and that we want to determine B, subject to satisfy some distance relation with A. According to the algebraic expressions of distances, dilation of A is an adequate tool for this. For instance if the knowledge expresses that $d(A, B) > n$, then B should be looked for in the complement of the dilation of A of size n. As another example, expressing that B should lay between a distance n_1 and a distance n_2 of A can be obtained by considering both minimum and maximum (Hausdorff) distances: the minimum distance should be greater than n_1 and the maximum distance should be less than n_2, which can be expressed by the set difference between two dilations of A of size n_2 and n_1 respectively. In cases where imprecision has to be taken into account, fuzzy dilations are used, with the corresponding equivalences with fuzzy distances. The extension to approximate distances calls for fuzzy structuring elements. We define these structuring elements through

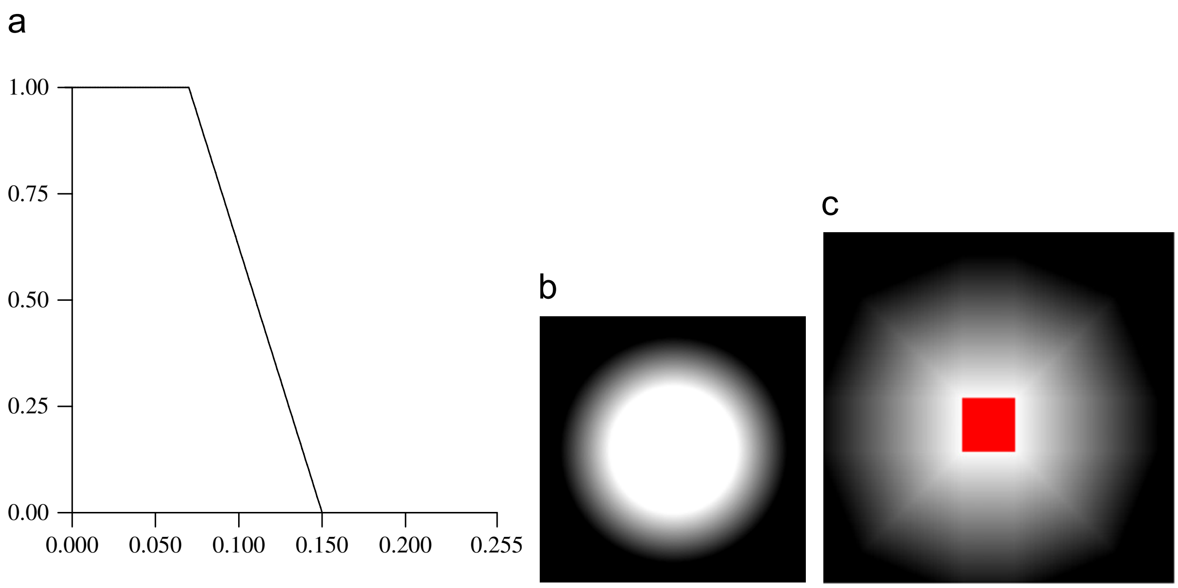


Fig. 7. (a) Fuzzy set on the distance space ($\mathbb{R}^+$) representing the semantics of "close to''. (b) Fuzzy structuring element derived from (a). (c) Fuzzy dilation of a square using the structuring element, representing the area of space close to the square.

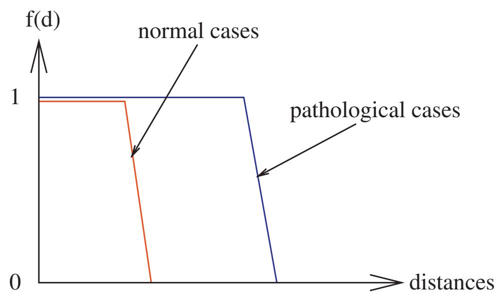


Fig. 8. Learning the relation "close to'' between putamen and caudate nucleus on normal cases and on pathological cases.

their membership function ν on $\mathcal{S}$. Structuring elements with a spherical symmetry can typically be used, where the membership degree only depends on the distance to the center of the structuring element. An example is illustrated in the case of the relation "close to'' in Fig. 7.

3.4. Fuzzy model learning

A key point of our approach is the instantiation of the parameters involved in the construction of the fuzzy representation of spatial relations, and consequently of our ontology. In [18] and in [1], this point is addressed as a learning problem. We assume, in the sequel, that in a first step a database of segmented images is available.

Let us detail the learning procedure for the second type of representations discussed in Section 3.1; its adaptation to the first type of representations is straightforward. Let K be the learning database, c an instance of K (image), O_c the set of segmented objects in c, R a spatial relation and μ_R the fuzzy subset in the image space corresponding to the relation R. For a given spatial relation, a leave-one-out procedure is used to learn the parameters of its fuzzy formulation μ_R. Since μ_R is defined in the spatial domain, we can directly compare μ_R with the target objects. This allows computing the fuzzy functions, which are of trapezoidal shapes in our ontology, involved in the construction of the spatial relations.

Let us detail the example of the relation "close to''. The training consists in computing the maximum distance from a point x of the target object B_c to the reference object A_c:

$$d^c_{\max} = \max_{x \in B_c} (d_{A_c}(x)).$$

Then the mean m and the standard deviation σ of $d^c_{\max}$ are computed over all instances c. The fuzzy interval f is then defined as the fuzzy set of the real line with kernel $[0, m]$ and support $[0, m + 2\sigma]$. This allows taking into account the variability of the parameters in the training set and overcoming, if necessary, the weak representativity of the database. A similar approach is applied for adjacency and directional relations. An application of this fuzzy learning approach to brain imaging is depicted in Fig. 8. More details can be found in [1].

4. Formal representation of spatial relations

We now describe the formalization of the different types of spatial relations which is necessary to clarify the user's diverse understanding of spatial relations and to automate spatial reasoning. As a formal language, we have chosen DL since it is compact and expressive and it is the basis of most ontological languages, in particular of the OWL language. The OWL DL formalism benefits from the compactness and the expressiveness of DL. It seems important to mention that other formalisms exist as for example conceptual graphs [65] for which fuzzy extensions have been proposed [55].

4.1. Spatial relations as concepts

One important entity of our ontology is the concept ***SpatialObject*** ($\mathsf{SpatialObject} \sqsubseteq \top$). Moreover, as mentioned in [50], the nature of spatial relations is twofold: they are concepts with their own properties but they are also links between concepts. For instance, the assertion "X is to the right of Y'' can be interpreted and represented in two different ways:

(1) As an "abstract'' relation between X and Y that is either true or false;
(2) As a physical spatial configuration between the two spatial objects X and Y.

As a consequence, we use a process of reification of spatial relations (illustrated in Fig. 10) as in [50]. A spatial relation is not considered in our ontology as a role (property) between two spatial objects but as a concept on its own (***SpatialRelation***). Fig. 9 represents the Venn diagram of the different concepts of the spatial relation ontology.

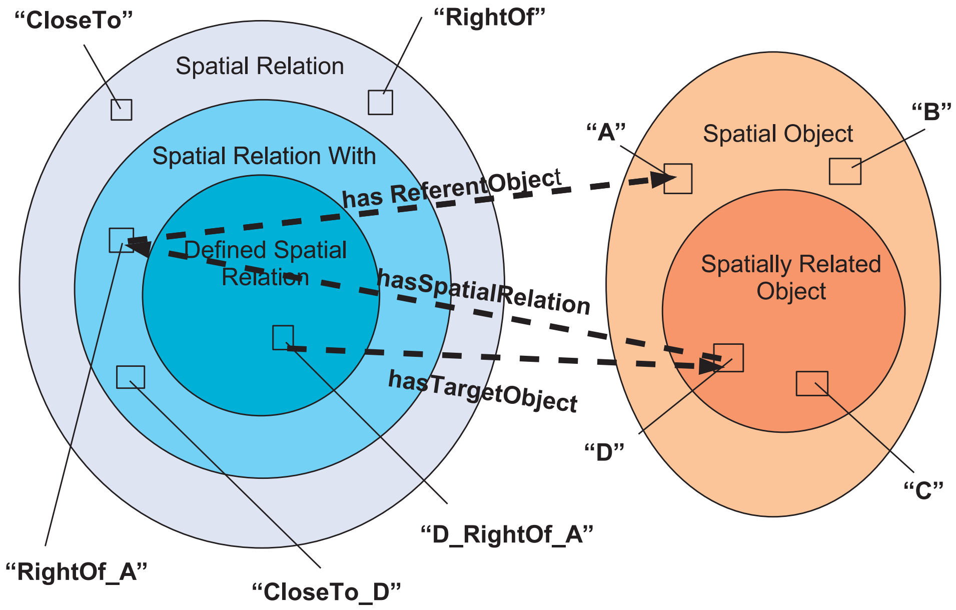


Fig. 9. Representation of the main concepts of the spatial relation ontology as a Venn diagram. This diagram illustrates the different concepts and how they are related. "A'' is a ***SpatialObject***, it is the ***ReferentObject*** of the ***Spatial Relation With*** concept "RightOf_A''. "D'' is a ***SpatialObject*** which has the property of having as ***Spatial Relation*** the relation "RightOf_A''.

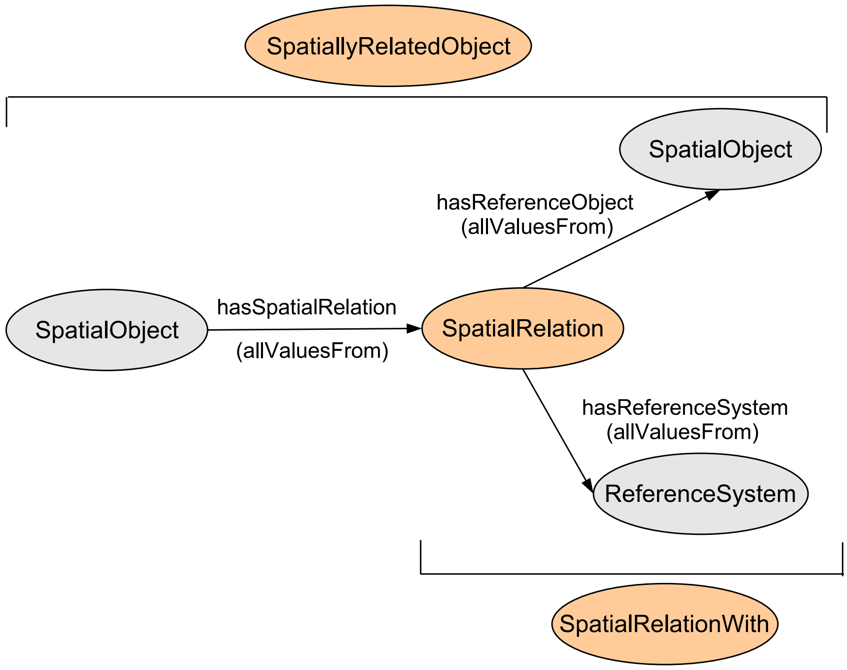


Fig. 10. Reification of spatial relations in the spatial relation ontology.

The notations used in the following are those of Table 1.

- A ***SpatialRelation*** is subsumed by the general concept ***Relation***. It is defined according to a ***ReferenceSystem***.

$$\begin{aligned}\mathsf{SpatialRelation} \sqsubseteq\ & \mathsf{Relation} \sqcap \\ & \ni \mathsf{type}.\{\mathsf{Spatial}\} \sqcap \\ & \exists\ \mathsf{hasReferenceSystem}.\mathsf{ReferenceSystem}\end{aligned}$$

  SpatialRelation subsumes ***TopologicalRelation*** and ***MetricRelation*** which itself subsumes ***DirectionalRelation*** and ***DistanceRelation*** as shown in Fig. 2. For ***BinarySpatialRelation***, we can also specify *inverse spatial relations* and properties such as *reflexivity*, *irreflexivity*, *symmetry*, *antisymmetry*, and *asymmetry* useful for qualitative spatial reasoning as shown in [50].
- We define the concept ***SpatialRelationWith*** which refers to the set of spatial relations which are defined according to at least one or more reference spatial objects.

$$\begin{aligned}\mathsf{SpatialRelationWith} \equiv\ & \mathsf{SpatialRelation} \sqcap \\ & \exists\ \mathsf{hasReferentObject}.\mathsf{SpatialObject} \sqcap \\ & \geqslant 1\ \mathsf{hasReferentObject}\end{aligned}$$

- We define the concept ***SpatiallyRelatedObject*** which refers to the set of spatial objects which have at least one spatial relation with another spatial object. This concept is useful to describe spatial configurations.

$$\begin{aligned}\mathsf{SpatiallyRelatedObject} \equiv\ & \mathsf{SpatialObject} \sqcap \\ & \exists\ \mathsf{hasSpatialRelation}.\mathsf{SpatialRelationWith} \sqcap \\ & \geqslant 1\ \mathsf{hasSpatialRelation}\end{aligned}$$

- At last, the concept ***DefinedSpatialRelation*** represents the set of spatial relations for which target and reference objects are defined.

$$\begin{aligned}\mathsf{DefinedSpatialRelation} \equiv\ & \mathsf{SpatialRelation} \sqcap \\ & \exists\ \mathsf{hasReferentObject}.\mathsf{SpatialObject} \sqcap \\ & \geqslant 1\ \mathsf{hasReferentObject} \sqcap \\ & \exists\ \mathsf{hasTargetObject}.\mathsf{SpatialObject} \sqcap \\ & = 1\ \mathsf{hasTargetObject}\end{aligned}$$

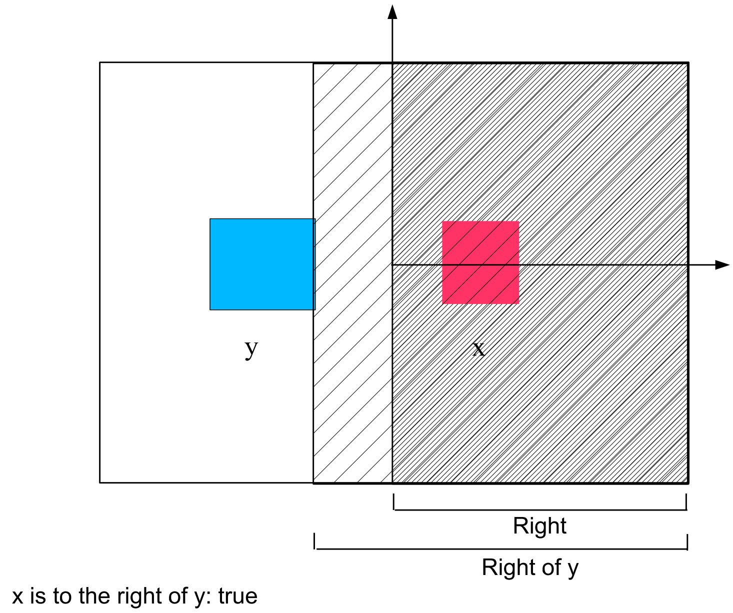


Fig. 11. Difference between three concepts: right (according to a reference frame), right of **y** (with respect to a reference object), and **x** is to the right of **y**.

This distinction between ***SpatialRelation***, ***SpatialRelationWith***, ***SpatiallyRelatedObject***, and ***DefinedSpatialRelation*** is important. Indeed, the meaning of *Right_Of*, *Right_Of_Y*, and *X is to the Right_Of_Y* is not the same as illustrated in Fig. 11 where an absolute frame of reference is considered. Let us describe the scene illustrated in this figure by using the spatial relation ontology. The concept ***Right_Of*** is defined as:

$$\begin{aligned}\mathsf{Right\_Of} \sqsubseteq\ & \mathsf{DirectionalRelation} \sqcap \\ & \mathsf{BinarySpatialRelation} \sqcap \\ & \exists\ \mathsf{inverse.Left\_Of}\end{aligned}$$

- y:SpatialObject and x:SpatialObject are two assertions that say that x and y are two spatial objects.
- The concept ***Right_Of_y*** is defined as $\mathsf{Right\_Of\_y} \equiv \mathsf{Right\_Of} \sqcap \ni \mathsf{hasReferentObject}.\{\mathsf{y}\}$. It represents the set of "right of'' relations that are possible with the object y.
- $\mathsf{x{:}SpatialObject} \sqcap \exists\ \mathsf{hasSpatialRelation.Right\_Of\_y}$ represents a spatial configuration. We can easily verify that x:SpatiallyRelatedObject.
- The concept $C_0 \equiv \mathsf{SpatialRelation} \sqcap \ni \mathsf{hasReferentObject}.\{\mathsf{y}\} \sqcap \ni \mathsf{hasTargetObject}.\{\mathsf{x}\}$ represents the set of spatial relations between the object x and the reference object y. $SP_1{:}\mathsf{CloseTo} \sqcap \ni \mathsf{hasReferentObject}.\{\mathsf{y}\} \sqcap \ni \mathsf{hasTargetObject}.\{\mathsf{x}\}$ and $SP_2{:}\mathsf{RightOf} \sqcap \ni \mathsf{hasReferentObject}.\{\mathsf{y}\} \sqcap \ni \mathsf{hasTargetObject}.\{\mathsf{x}\}$ are two individuals belonging to C_0.

Ontology implementation: The ontology of spatial relations has been developed with the software Protégé OWL [5] and can be obtained on demand. Fig. 2 represents a part of the hierarchy of the different spatial relations.

4.2. Integration of the fuzzy models

As in [56], we follow an approach of modular semantics for integrating the fuzzy model of spatial relations with the spatial relation ontology. We combine the two various formalisms in a modular way, thus we can combine and use the best of each of them. Moreover, the separation of the abstract domain (the spatial relation ontology) from its concrete domain on which fuzzy representations are defined contributes to reducing the semantic gap. This integration consists in linking concepts of the spatial relation ontology to their corresponding physical fuzzy representation in the image domain. Of course, the fuzzy representation depends on the type of question. For instance, for the relation "Right of R'', we are interested in the area of the image space where the relation right of R can be satisfied. Therefore this concept is

[5] http://protege.stanford.edu/plugins/owl/.

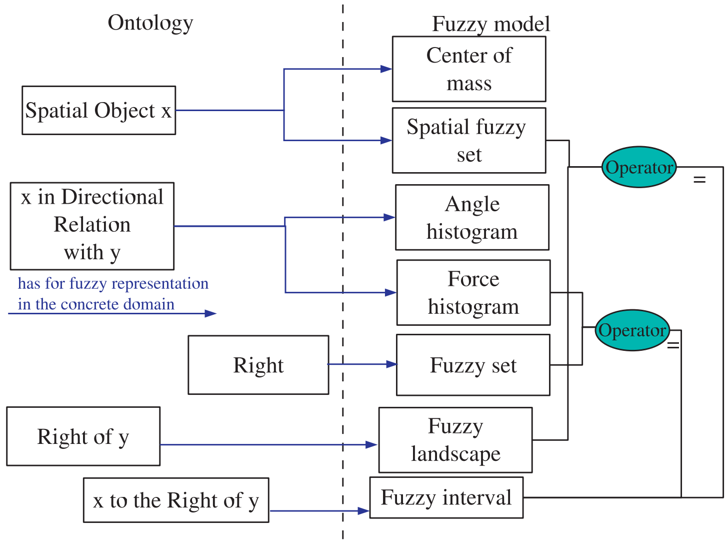
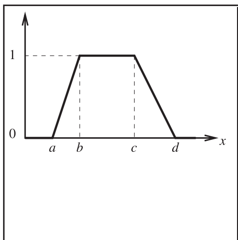


Fig. 12. Syntactic integration between the spatial relation ontology and the fuzzy representation model for directional relations.



$$Trz(x; a, b, c, d) = \begin{cases} 0 & \text{if } x \leq \text{a} \\ (x-a)/(b-a) & \text{if } x \in \text{[a,b]} \\ 1 & \text{if } x \in \text{[b,c]} \\ (d-x)/(d-c) & \text{if } x \in \text{[c,d]} \\ 0 & \text{if } x \geq \text{d} \end{cases}$$

```
<xsd:complexType name="TrapezoidalFuzzySet" >
<xsd:sequence>
<xsd:element name="a" type="xsd:float"/>
<xsd:element name="b" type="xsd:float"/>
<xsd:element name="c" type="xsd:float"/>
<xsd:element name="d" type="xsd:float"/>
</xsd:sequence>
</xsd:complexType>
```

Fig. 13. A trapezoidal fuzzy set, its membership function and description of the corresponding fuzzy XML datatype.

linked to a fuzzy landscape representation (Fig. 6 (b right)), whereas the relation "Right of'' is linked to a fuzzy subset of the set of angles representing the semantics of the relation. In the first case the concrete domain is the image support, while in the second one it is the real line. The fuzzy sets defined on these concrete domains provide the semantics of the relation.

Fig. 12 represents the nature of integration links for directional relations. These links are implemented by the relation *has for fuzzy representation in the concrete domain*. In this figure, operators correspond to comparison operators.

Let us illustrate how to interpret this figure on a simple example, and consider the following anatomical knowledge: "the right putamen is to the right of the lateral ventricles''. Let us consider a scenario where the lateral ventricles have been recognized in an image. The "Spatial Object lateral ventricle'' of the ontology is then linked to its representation in the concrete domain (image support), which can be a fuzzy or a crisp set. Let us then consider the concept "Right'' in the ontology. Its semantics is provided by a fuzzy set in the image domain, according to the usual reference system used to describe anatomy, defining for each point to which degree it is to the right of some reference point. This fuzzy set is then considered as a structuring element and used in a morphological dilation to define the region of space to the right of the lateral ventricles, according to [7]. This new fuzzy set (fuzzy landscape) defines the semantics of the ontological concept "Right of the lateral ventricles''. This fuzzy region can be used to drive the recognition of the right putamen (see Section 5). In case the putamen is known in the image, again the concept "Spatial Object right putamen'' is linked to its spatial representation in the image, which can be compared, using appropriate operators, to the region to the right of the lateral ventricles to assess the degree of satisfaction of the relation between both objects.

As the introduction of concrete domains in OWL is based on XML Schema datatypes, we have defined a set of XML Schema datatypes in order to describe fuzzy sets, fuzzy numbers, fuzzy intervals, and spatial fuzzy sets. Fig. 13 describes the fuzzy XML schema datatypes used to describe trapezoidal fuzzy sets.

For instance, the spatial relation "Close to'' described in Fig. 7 is linked to a trapezoidal fuzzy set (represented in Fig. 7 (a)) and described by the fuzzy datatype:

```
<fxsd:TrapezoidalFuzzySet name="close˙to">
<fxsd:a value="0.0"/ >
<fxsd:b value="0.0"/ >
<fxsd:c value="0.1"/ >
<fxsd:d value="0.15"/ >
< /fxsd:TrapezoidalFuzzySet>
```

where fxsd is the namespace for the fuzzy XML schema datatype definitions.

4.3. Fusion and reasoning

One of the advantages of using spatial concrete domains is the separation of semantics, which is very useful for knowledge representation and for reasoning.

All concepts that are included in the ontology are generic in the sense of their formal definition. Only their fuzzy representations (and their semantics) may vary from one domain to another one, and can be learned as explained in Section 3.4. For example a relation such as "close to'' will not have the same meaning in a GIS context or in the context of interpretation of satellite images or of medical images. This difference is expressed in the fuzzy model (for instance, we only have to adapt the values of a, b, c, d in the trapezoidal fuzzy sets, see Fig. 13), whereas the ontology of spatial relations remains a support for more general reasoning. At this stage of development, the ontology contains the most used spatial relations. Concepts that are not encoded cannot be used in the reasoning, but the ontology could be easily extended to add new ones. We describe in Section 5 how this spatial relation ontology can be used to describe structures in specific domains. Moreover, image interpretation tasks can also benefit from automatic reasoning on ontologies and from fuzzy logic reasoning.

General automatic reasoning tasks on ontologies include concept consistency, concept subsumption to build inferred concepts taxonomy, instance classification and retrieval, parent and children concept determination, and answering queries over ontology classes and instances. To perform these reasoning tasks, we can use reasoning tools such as RACER [37], FACT++ [6] or PELLET. [7] In the current implementation, only this classical reasoning is used. Recent works on fuzzy DL reasoners [8] could be used in future works to improve the proposed framework and to enable the reasoning on fuzzy models.

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 [31,32] 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 [6].

[6] http://owl.man.ac.uk/factplusplus/.
[7] http://www.mindswap.org/2003/pellet/.
[8] http://gaia.isti.cnr.it/∼straccia/software/fuzzyDL/intro.html or see [25].

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.

5. Illustration: model-driven segmentation of brain structures in MRI

In this section, we show how the proposed approach can be exploited in the context of structural pattern recognition. As an illustration, we consider a real medical problem in brain imaging: internal brain structure recognition in magnetic resonance volumes. The motivation of this choice is threefold. (i) In this domain, to establish an accurate diagnosis, it is desirable to have a description of the pathology as well as its influence on the surrounding brain structures, in particular through their spatial relations. (ii) Internal brain structures have the same appearance (they are constituted of gray matter) and are often prone to shape variability. The use of spatial relations may then help to solve the ambiguity and improves detection and recognition. (iii) The elaboration of the domain ontology can benefit from the large amount of existing knowledge formalization models, some of them based on ontological engineering tools (such as the FMA [59]), that emerged from the medical informatics research field. While neuro-anatomy has not been much developed in these models, it is largely described in textbooks [74] and dedicated sites, [9] 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 the use of the ontology of spatial relations for enriching the ontology of the domain (cerebral anatomy in this context).

Fig. 14 represents how the spatial relation ontology can be used to describe structures in specific domains. In this figure, the ontology is imported in an ontology of the brain anatomy (excerpt of the Foundational Model of Anatomy (FMA) [59]) and is used to describe the spatial organization of brain anatomical components. We consider that each physical anatomical component is a spatial object. Then, spatial relations between these different spatial objects are described by using the spatial relation ontology. For instance, as illustrated in Fig. 14, the right caudate nucleus is to the right and close to the right ventricle and above the right thalamus.

Moreover, the semantic enrichment by the fuzzy representations of spatial relations, learned on a database of examples, makes it possible to formalize the ontology concepts in an operational way, that facilitates pattern recognition and image interpretation.

In previous works [5,11,18], two methods have been proposed for recognizing brain structures, a global one and a sequential one. The choice of the structures to recognize and the spatial relations that guide the recognition was entirely supervised. This constraint can now be relaxed by exploiting the features of the proposed ontology, and this constitutes an important and concrete outcome of this paper. In the following, we consider crisp spatial objects and fuzzy spatial relations.

5.1. Sequential approach

In a sequential approach [11,18], the structures are recognized successively. To detect a structure, its spatial relations with the previously recognized structures are used to reduce the search space to image areas that satisfy these relations.

Let us detail the process in the case of the detection and recognition of the right caudate nucleus assuming that the right lateral ventricle has already been extracted. The situation is represented in Fig. 15. [10]

- A first step consists in extracting information from the domain ontology by querying it. The goal of the query is to find the spatial relations involving the right lateral ventricle and the right caudate nucleus. As the first one is already

[9] http://www.chups.jussieu.fr/ext/neuranat/index.html for instance.

[10] Here we do not use the "left is right'' convention usually adopted in the medical imaging community, but for the sake of simplicity we denote by "right'' structures that are on the right side in the figures (i.e. on the left side of the body).

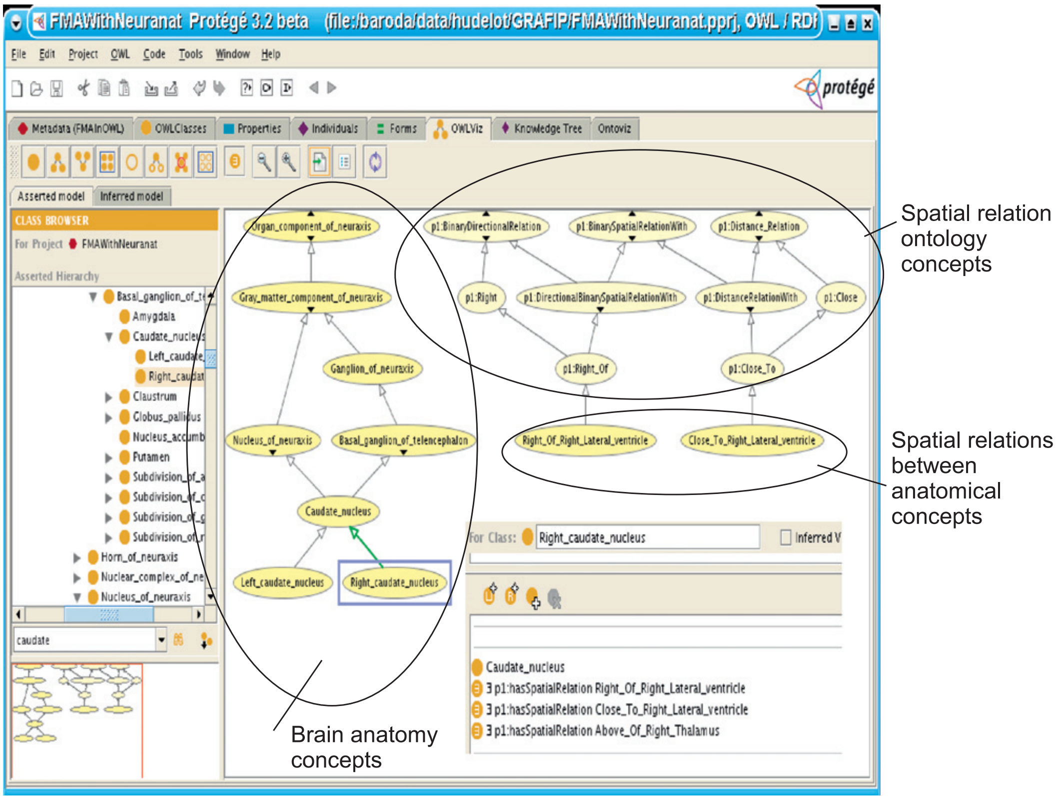


Fig. 14. Part of an ontology of the brain anatomy (excerpt of the FMA [59]). The concepts of the spatial relation ontology are prefixed by **p1**.

extracted and recognized, it is taken as a reference object. As a querying language, we use the nRQL language provided by RACER [37]. The nRQL request is expressed as:

```
(tbox-retrieve (?x)(and
(?y Right_Caudate_nucleus)
(?y ?x hasSpatialRelation)
(?z Right_Lateral_ventricle)
(?x ?z hasReferenceObject)))
```

An answer to such a query using our enriched domain ontology is: ***Right_Of_Right_Lateral_ventricle*** and ***Close_To_Right_Lateral_ventricle***. Indeed, according to the domain ontology "the right caudate nucleus is to the right and close to the right lateral ventricle and above the right thalamus'' (see Fig. 15). Note that the last part of this knowledge is not used here since the thalamus is not recognized yet.

- Then, according to the ontology of spatial relations, concepts such as ***Right_Of_Right_Lateral_ventricle*** or ***Close_To_Right_Lateral_ventricle*** are derived from the concept ***SpatialRelationWith*** and their syntactic integration (i.e. fuzzy semantics in the image domain) corresponds here to a *fuzzy landscape* (see Fig. 12). The fuzzy semantics is used to guide the operating mode (in this case, a fuzzy dilation with a structuring element defining the right direction). A similar reasoning is used for the relation **close to**, leading to another morphological operation.
- In the image domain, the search space of the "right caudate nucleus'' corresponds to the area to the right and close to the right lateral ventricle, derived from the conjunctive fusion of the results of the two morphological operations, still performed in the spatial domain (Fig. 16).

The next step consists in segmenting the caudate nucleus. The fuzzy region of interest derived from the previous steps is used to constrain the search space and to drive the evolution of a deformable model. An initial surface is deformed toward the solution under a set of forces, including forces derived from spatial relations. The detailed description of this segmentation process is outside the scope of this paper [2,18]. Fusion aspects are involved when several types of knowledge are expressed for the same object. Spatial representations of each knowledge type have to be combined in

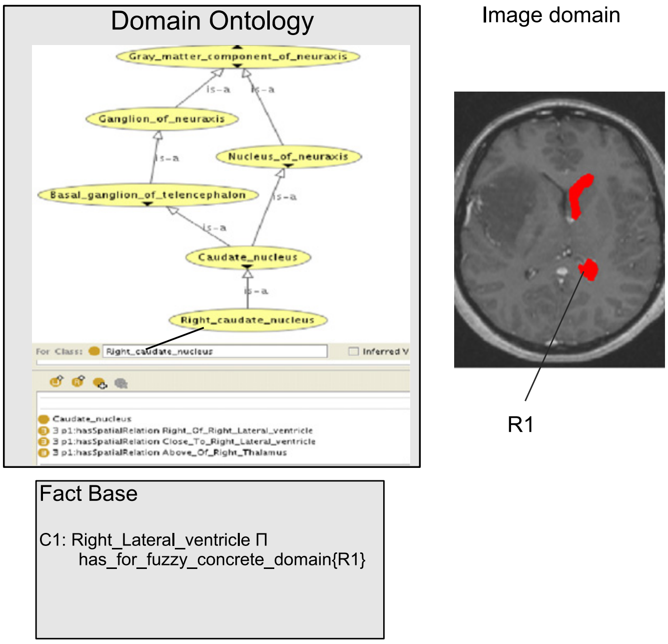


Fig. 15. The right lateral ventricle corresponds to the spatial region R1 in the image. The domain ontology describes spatial relations between the right caudate nucleus and the right lateral ventricle. These relations will be exploited to segment the right caudate nucleus.

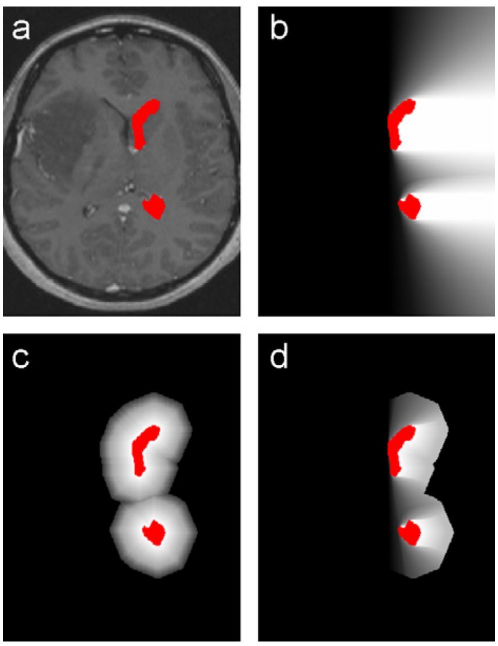


Fig. 16. (a) The right ventricle is superimposed on one slide of the original image. The search space of the object "caudate nucleus'' corresponds to the conjunctive fusion of the spatial relations "to the right of the right ventricle'' (b) and "close to the right ventricle'' (c). The fusion result is shown in (d).

order to define a search space which satisfies the fusion of the constraints (in the previous example, a constraint on distance and a constraint on direction). Fusion between different forces is also involved in the evolution process of the deformable model.

More generally, this type of approach and the use of spatial representations of spatial relations are appropriate for problems of scene navigation where the knowledge about the scene is incrementally refined when more and more

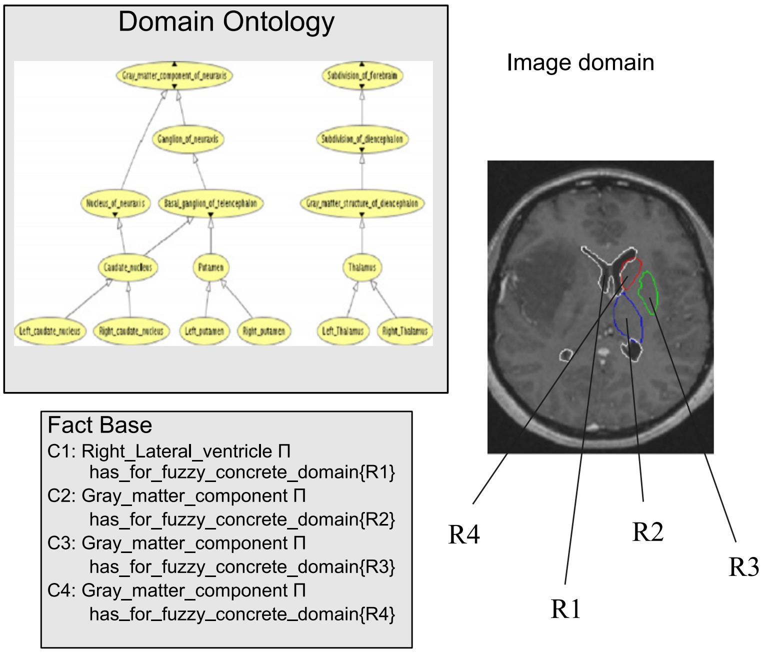


Fig. 17. The right lateral ventricle corresponds to the spatial region R1 on image. The domain ontology describes spatial relations between several gray nuclei and the lateral ventricles. These relations will be exploited to identify each individual structure.

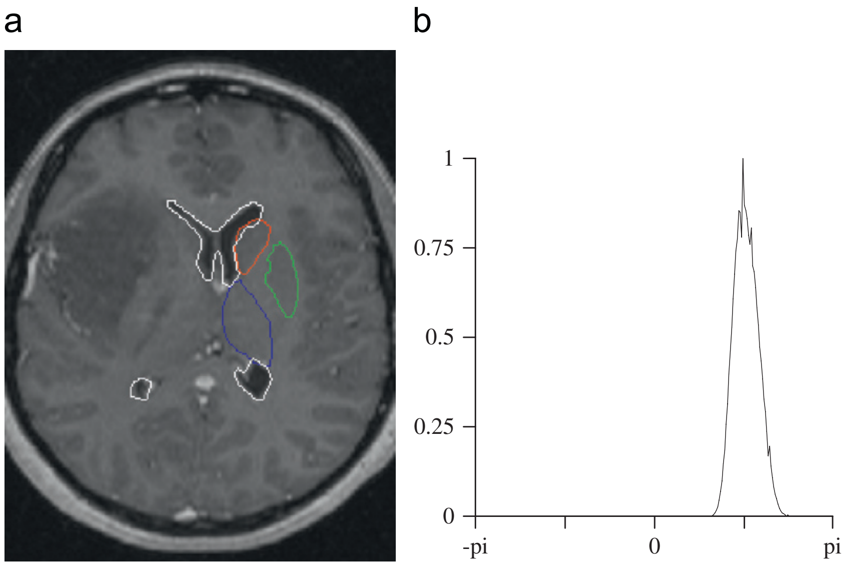


Fig. 18. (a) Segmentation of some structures. (b) Histogram of angles of the structure in red (R4 in Fig. 18) and the structure in blue (R2). The comparison between this histogram and the semantic of the relation “below’’ makes it possible to compute to which degree this relation between the two structures is satisfied (0.9 here). Hence the blue structure should be a structure that is below another one in the ontology. Similar computation of other relations lead to the recognition of the segmented structures: caudate nucleus in red, putamen, in green and thalamus in blue.

objects are recognized: starting with simple objects, the scene structure is learned progressively and exploited in order to detect and recognize objects that would have been difficult to recognize directly.

This segmentation approach has been evaluated for several brain structures on normal brain images in [18]. The order of the structures to be segmented and the type of knowledge useful for recognizing each of them was provided by the user. As illustrated above, this step can now be completely automated.

5.2. Global approach

While in the sequential approach, segmentation and recognition are performed simultaneously, in a global approach [5], several objects are first extracted from the image using a segmentation method, and then recognized. The recognition can be achieved by assessing if the spatial relations between two objects x and y are those existing in the domain ontology. As for the sequential approach, let us detail the process in the case of Fig. 17.

- From the segmentation process (not described here), three structures that belong to the grey nuclei are extracted. The first step consists in assessing spatial relations between these structures. For the sake of simplicity we focus on relative directions. The situation is represented in Fig. 18.
- We are interested in finding all the directional spatial relations between R1, R2, R3, R4, where R1 represents the lateral ventricles and R2–R4 the three regions to be labeled. The ontology of spatial relations is used to select an adequate representation for question 1, i.e the fuzzy representation of concepts "X in directional relation with Y'' (see Section 3.1). The derived syntactic integration corresponds for instance here to a *histogram of angles* (see Fig. 12). By using a *fuzzy interval* operating mode, the degrees of satisfaction of several directional relations between the segmented regions are computed. In this example, the following assertions yield high degrees of satisfaction: "R2 is to the right of R1'', "R2 is below R4'', "R3 is to the right of R1'', "R3 is to the right of R4'', and "R4 is to the right of R1''.
- The description of the concepts C1, C2, C3, and C4 (Fig. 18) is completed with the predominant directional relations between R1, R2, R3, R4 and then are classified in the hierarchy using reasoners. This allows us to label, i.e. to recognize each individual structure. In the example, structures R2, R3 and R4 are recognized as thalamus, putamen and caudate nucleus, respectively.

6. Conclusion

The contribution of this paper is twofold. First, an ontology of spatial relations is proposed, along with its integration with existing domain ontologies, such as the FMA for anatomical concepts. Secondly, this ontology is linked to fuzzy representations which define the semantics of the spatial concepts, in particular the spatial relations. This link is implemented via concrete domains. This allows adapting the semantics to a particular application, while the ontology remains general. Different types of reasoning then become possible: (i) a quite general reasoning may consist in classifying or filtering ontological concepts to answer 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, recognition. The potential of these types of reasoning and of the proposed approach has been illustrated on a simple example in brain imaging. The enriched ontology contributes to reducing the semantic gap, which is a difficult and still open problem in image interpretation, and 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.

It should be noted that all concepts that are included in the ontology are generic. Only their fuzzy representations (and their semantics) may vary from one domain to another one, and can be learned. At this stage of development, the ontology contains the most used spatial relations. Concepts that are not encoded cannot be used in the reasoning, but the ontology could be easily extended to add new ones. What might be more difficult is to define the proper semantics and the associated fuzzy representation. For instance, our work on the relation "between'' [10] has shown that the semantics can vary a lot depending on the context, but also on the shape of the objects. Modeling complex relations is still an open question for most of them.

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References

[1] J. Atif, C. Hudelot, G. Fouquier, I. Bloch, E. Angelini, From generic knowledge to specific reasoning for medical image interpretation using graph-based representations, in: Internat. Joint Conf. on Artificial Intelligence IJCAI'07, Hyderabad, India, January 2007, pp. 224–229.

[2] J. Atif, O. Nempont, O. Colliot, E. Angelini, I. Bloch, Level set deformable models constrained by fuzzy spatial relation, in: Information Processing and Management of Uncertainty in Knowledge-Based Systems, IPMU, Paris, France, 2006, pp. 1534–1541.
[3] F. Baader, D. Calvanese, D. McGuinness, D. Nardi, P. Patel-Schneider, The Description Logic Handbook: Theory, Implementation and Applications, Cambridge University Press, Cambridge, 2003.
[4] J. Bateman, S. Farrar, Towards a generic foundation for spatial ontology, in: International Conference on Formal Ontology in Information Systems (FOIS-2004), Trento, Italy, 2004, pp. 237–248.
[5] E. Bengoetxea, P. Larranaga, I. Bloch, A. Perchant, C. Boeres, Inexact graph matching by means of estimation of distribution algorithms, Pattern Recogn. 35 (2002) 2867–2880.
[6] I. Bloch, Information combination operators for data fusion: a comparative review with classification, IEEE Trans. Systems Man Cybernet. 26 (1) (1996) 52–67.
[7] I. Bloch, Fuzzy relative position between objects in image processing: a morphological approach, IEEE Trans. Pattern Anal. Mach. Intelligence 21 (7) (1999) 657–664.
[8] I. Bloch, On fuzzy distances and their use in image processing under imprecision, Pattern Recogn. 32 (11) (1999) 1873–1895.
[9] I. Bloch, Fuzzy spatial relationships for image processing and interpretation: a review, Image Vision Comput. 23 (2) (2005) 89–110.
[10] I. Bloch, O. Colliot, R. Cesar, On the ternary spatial relation between, IEEE Trans. Systems Man Cybernet. SMC-B 36 (2) (2006) 312–327.
[11] I. Bloch, T. Géraud, H. Maître, Representation and fusion of heterogeneous fuzzy information in the 3D space for model-based structural recognition—application to 3D brain imaging, Artificial Intelligence 148 (2003) 141–175.
[12] I. Bloch, H. Maître, M. Anvari, Fuzzy adjacency between image objects, Internat. J. Uncertainty, Fuzziness and Knowledge-Based Systems 5 (6) (1997) 615–653.
[13] I. Bloch, A. Ralescu, Directional relative position between objects in image processing: a comparison between fuzzy approaches, Pattern Recogn. 36 (2003) 1563–1582.
[14] A. Burgun, Desiderata for domain reference ontologies in biomedicine, J. Biomed. Informatics 39 (2006) 307–313.
[15] R. Casati, B. Smith, A.C. Varzi, Ontological tools for geographic representation, in: N. Guarino (Ed.), Formal Ontology in Information Systems, IOS Press, Amsterdam, 1998, pp. 77–85.
[16] R. Cesar, E. Bengoetxea, I. Bloch, Inexact graph matching using stochastic optimization techniques for facial feature recognition, in: Internat. Conf. on Pattern Recognition ICPR 2002, Vol. 2, Québec, August 2002, pp. 465–468.
[17] A.G. Cohn, D.C. Hogg, B. Bennett, V. Devin, A. Galata, D.R. Magee, C. Needham, P. Santos, Cognitive vision: integrating symbolic qualitative representations with computer vision, in: Cognitive Vision Systems: Sampling the Spectrum of Approaches, in: Lecture Notes in Computer Science, Springer, Heidelberg, 2005, pp. 211–234.
[18] O. Colliot, O. Camara, I. Bloch, Integration of fuzzy spatial relations in deformable models—application to brain MRI segmentation, Pattern Recogn. 39 (2006) 1401–1414.
[19] S. Coradeschi, A. Saffiotti, Anchoring symbols to vision data by fuzzy logic, in: A. Hunter, S. Parsons (Eds.), ECSQARU'99, in: Lecture Notes in Computer Science, Vol. 1638, London, July 1999, Springer, Berlin, pp. 104–115.
[20] D. Crevier, R. Lepage, Knowledge-based image understanding systems: a survey, Comput. Vision Image Understanding 67 (2) (1997) 160–185.
[21] P. da Costa et al. (Eds). Proc. ISWC Workshop on Uncertainty Reasoning for the Semantic Web, Galway, Ireland, 2005.
[22] 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, April 2005.
[23] O. Dameron, B. Gibaud, X. Morandi, Numeric and symbolic knowledge representation of cerebral cortex anatomy: methods and preliminary results, Surgical Radiologic Anatomy 26 (3) (2004) 191–197.
[24] M. d'Aquin, J. Lieber, 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, pp. 255–262.
[25] M. d'Aquin, J. Lieber, A. Napoli, Adaptation knowledge acquisition: a case study for case-based decision support in oncology, Comput. Intelligence 22 (3/4) (2006) 161–176.
[26] S. Dasiopoulou, V. Mezaris, I. Kompatsiaris, V.K. Papastathis, M.G. Strintzis, Knowledge-assisted semantic video object detection, IEEE Trans. Circuits Systems Video Tech. 15 (10) (2005) 1210–1224.
[27] Z. Ding, Y. Peng, R. Pan, A Bayesian approach to uncertainty modelling in OWL ontology, in: Internat. Conf. on Advances in Intelligent Systems—Theory and Applications (AISTA2004), Luxembourg-Kirchberg, Luxembourg, 2004.
[28] P.F. Dominey, J.D. Boucher, T. Inui, Building an adaptive spoken language interface for perceptually grounded human–robot interaction, in: Fourth IEEE/RAS Internat. Conf. on Humanoid Robots, Vol. 1, 2004, pp. 168–183.
[29] M. Donnelly, T. Bittner, C. Rosse, A formal theory for spatial representation and reasoning in biomedical ontologies, Artificial Intelligence Medicine 36 (1) (2006) 1–27.
[30] D. Dubois, H. Prade, Fuzzy Sets and Systems: Theory and Applications, Academic Press, New-York, 1980.
[31] D. Dubois, H. Prade, A review of fuzzy set aggregation connectives, Inform. Sci. 36 (1985) 85–121.
[32] D. Dubois, H. Prade, R. Yager, Merging fuzzy information, in: J.C. Bezdek, D. Dubois, H. Prade (Eds.), Handbook of Fuzzy Sets Series, Approximate Reasoning and Information Systems, Kluwer, Dordrecht, 1999(Chapter 6).
[33] J. Freeman, The modelling of spatial relations, Comput. Graphics Image Processing 4 (2) (1975) 156–171.
[34] C. Freksa, M. Knauff, B. Krieg-Bruckner, B. Nebel, T. Barkowsky, Spatial Cognition IV—Reasoning, Action, Interaction, in: Springer Series in Perception Engineering, Springer, Berlin, 2004.
[35] T.R. Gruber, Towards principles for the design of ontologies used for knowledge sharing, in: N. Guarino, R. Poli (Eds.), Formal Ontology in Conceptual Analysis and Knowledge Representation, Deventer, The Netherlands, Kluwer Academic Publishers, Dordrecht, 1993.
[36] V. Haarslev, C. Lutz, R. Moller, Foundations of spatioterminological reasoning with description logics, in: Sixth Internat. Conf. on Principles of Knowledge Representation and Reasoning, Trento, Italy, 1998, pp. 112–123.

[37] V. Haarslev, R. Moller, RACER system description, in: Proceedings of the Internat. Joint Conf. on Automated Reasoning (IJCAR 2001), 2001.
[38] D. Han, B.J. You, Y.S.E. Kim, I.L.H. Suh, A generic shape matching with anchoring of knowledge primitives of object ontology, in: M. Kamel, A. Campilho (Eds.), ICIAR 2005, Lecture Notes in Computer Science, Vol. 3646, 2005, pp. 473–480.
[39] S. Harnad, The symbol grounding problem, Phys. 42 (1990) 335–346.
[40] S. Hazarika, A.G. Cohn, A taxonomy for spatial vagueness: an alternative egg-yolk interpretation, in: Spatial Vagueness, Uncertainty and Granularity Symposium, Ogunquit, Maine, USA, 2001.
[41] A. Herskovits, Language and Spatial Cognition. A Interdisciplinary Study of the Prepositions in English, Cambridge University Press, Cambridge, MA, 1986.
[42] S. Holldobler, T.D. Khang, H.P. Storr, A fuzzy description logic with hedges as concept modifiers, Proc. InTech/VJFuzzy 2002 (2002) 25–34.
[43] C. Hudelot, Towards a cognitive vision platform for semantic image interpretation; application to the recognition of biological organisms, Ph.D. Thesis, University of Nice Sophia Antipolis, France, April 2005.
[44] J.M. Keller, X. Wang, A fuzzy rule-based approach to scene description involving spatial relationships, Comput. Vision Image Understanding 80 (1) (2000) 21–41.
[45] R.L. Klatzky, Allocentric and egocentric spatial representations: definitions, distinctions, and interconnections, in: Spatial Cognition, Lecture Notes in Computer Science, Vol. 1404, 1998, pp. 1–18.
[46] E. Klien, M. Lutz, The role of spatial relations in automating the semantic annotation of geodata, in: A.G. Cohn, D.M. Marks (Eds.), Conference on Spatial Information Theory (COSIT 2005), Lecture Notes in Computer Science, Vol. 3693, 2005, pp. 133–148.
[47] S.K. Kopparapu, U.B. Desai, Bayesian approach to image interpretation, The Springer International Series in Engineering and Computer Science, 2001.
[48] B. Kuipers, Modeling spatial knowledge, Cognitive Sci. 2 (1978) 129–153.
[49] B.J. Kuipers, T.S. Levitt, Navigation and mapping in large-scale space, AI Magazine 9 (2) (1988) 25–43.
[50] F. Le Ber, A. Napoli, The design of an object-based system for representing and classifying spatial structures and relations, J. Universal Comput. Sci. 8 (8) (2002) 751–773.
[51] Y. Li, B. Xu, J. Lu, D. Kang, P. Wang, A family of extended fuzzy description logics, in: 29th Annual International Computer Software and Applications Conference (COMPSAC'05), Vol. 1, Los Alamitos, CA, USA, IEEE Computer Society, 2005, pp. 221–226.
[52] P. Matsakis, L. Wendling, A new way to represent the relative position between a real objects, IEEE Trans. Pattern Anal Mach Intelligence 21 (7) (1999) 634–642.
[53] J.-L. Metzger, F. Le Ber, A. Napoli, Modeling and representing structures for analyzing spatial organization in agronomy, in: International Conference on Conceptual Structures (ICCS 2003), Lecture Notes in Computer Science, Vol. 2746, Dresden, Germany, 2003, pp. 215–228.
[54] K. Miyajima, A. Ralescu, Spatial organization in 2D segmented images: representation and recognition of primitive spatial relations, Fuzzy Sets and Systems 65 (1994) 225–236.
[55] P. Mulhem, W.K. Leow, Y.K. Lee, Fuzzy conceptual graphs for matching images of natural scenes, in: IJCAI, 2001, pp. 1397–1404.
[56] G. Nagypal, B. Motik, A fuzzy model for representing subjective and vague temporal knowledge ontologies, in: Internat. Conf. on Ontologies, Databases and Applications of Semantics, Catania, Sicily, Italy, 2003.
[57] D. Randell, Z. Cui, A. Cohn, A spatial logic based on regions and connection, in: B. Nebel, C. Rich, W. Swartout (Eds.), Principles of Knowledge Representation and Reasoning KR'92, Kaufmann, San Mateo, CA, 1992, pp. 165–176.
[58] A. Rosenfeld, R. Klette, Degree of adjacency or surroundness, Pattern Recogn. 18 (2) (1985) 169–177.
[59] C. Rosse, J.L.V. Mejino, A reference ontology for bioinformatics: The foundational model of anatomy, J. Biomedical Informatics 36 (2003) 478–500.
[60] E. Sanchez, (Ed.), Fuzzy Logic and the Semantic Web, Elsevier, Amsterdam, 2006.
[61] B. Scherrer, M. Dojat, F. Forbes, C. Garbay, Segmentation markovienne distribuée et coopérative des tissus et structures présents dans des IRM cérébrales, in: Reconnaissance des Formes et Intelligence Artificielle, RFIA'06, Tours, France, January 2006.
[62] S. Schulz, U. Hahn, 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, pp. 779–783.
[63] C.R. Shyu, P. Matsakis, Spatial lesion indexing for medical image databases using force histograms, in: Computer Vision and Pattern Recognition (CVPR 2001), Vol. 2, Kauai, Hawaii, 2001. pp. 603–608.
[64] A.W.M. Smeulders, M. Worring, S. Santini, A. Gupta, R. Jain, Content-based image retrieval at the end of the early years, IEEE Trans. Pattern Anal. Machine Intelligence 22 (12) (2000) 1349–1380.
[65] J.F. Sowa, Conceptual structures: information processing in mind and machine, Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1984.
[66] J.G. Stell, Part and complement: fundamental concepts in spatial relations, Ann. Math. Artif. Intelligence 41 (1) (2004) 1–17.
[67] G. Stoilos, G. Stamou, J.Z. Pan, Handling imprecise knowledge with fuzzy description logic, in: International Workshop on Description Logics (DL 06), Lake District, UK, 2006, pp. 119–126.
[68] U. Straccia, Description logics with fuzzy concrete domains, in: F. Bachus, T. Jaakkola (Eds.), 21st Conf. on Uncertainty in Artificial Intelligence (UAI-05), AUAI Press, Edinburgh, Scotland, 2005, pp. 559–567.
[69] U. Straccia, A fuzzy description logic for the semantic web, in: E. Sanchez (Ed.), Fuzzy Logic and the Semantic Web, Capturing Intelligence, Elsevier, Amsterdam, 2006, pp. 73–90, (Chapter 4).
[70] L. Talmy, How language structures space, in: H.L. Pick, L.P. Acredolo (Eds.), Spatial Orientation: Theory, Research and Application, Plenum Press, New York, 1983.
[71] M. Thonnat, Knowledge-based techniques for image processing and image understanding, J. de Physique EDP Sciences 4 (12) (2002) 189–235.
[72] C. Town, Ontological inference for image and video analysis, Machine Vision Appl. 17 (2) (2006) 94–115.
[73] L. Vieu, Spatial representation and reasoning in artificial intelligence, in: O. Stock (Ed.), Spatial and Temporal Reasoning, Kluwer, Dordrecht, 1997, pp. 5–41.

[74] S.G. Waxman, Correlative Neuroanatomy, 24th ed., McGraw-Hill, New York, 2000.
[75] Y. Yang, J. Calmet, Ontobayes: an ontology-driven uncertainty model, in: Internat. Conf. on Intelligent Agents, Web Technology and Internet Commerce (IAWTIC'05), Vol. 1, 2005, pp. 457–464.
[76] P. Zweigenbaum, B. Bachimont, J. Bouaud, J. Charlet, J.F. Boisvieux, Issues in the structuring and acquisition of an ontology for medical language understanding, Methods Inform. Med. 34 (1) (1995) 2.