Spatial Reasoning with Fuzzy Ontologies

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Abstract

Ontologies, defined as a "formal representation of a shared conceptualization", are a popular formalism for knowledge representation in Artificial Intelligence combining the expressive power of graph-based representations with the formal underpinnings of Description Logics (DLs). They have gained popularity after their extensive use in the Semantic Web, producing the standard languages RDF (Resource Description Framework) and OWL (Ontology Web Language).

Ontologies are useful in problems requiring flexible, shareable and extensible knowledge models. A paradigmatic case is Data and Information Fusion (DIF), which studies theories and methods to combine data streaming out from multiple sensors and other relevant sources to obtain a better situational picture than would be achieved by using a single input [11]. Ontologies have been used in DIF for different tasks: exchanging messages between agents [7], representing scene objects at different levels [8], modeling complex part-whole relationships [13], contextual information exploitation [10], reasoning for situation recognition and assessment [9], and so forth. Besides, ontologies have been extended to provide support for qualitative spatial knowledge by means of geometrical –e.g. *A is near B*– and topological properties –e.g. *A is inside B*.

Ontologies cannot directly manage imprecise knowledge, which is inherent to several real-world problems, and particularly to DIF applications. For example, we would like to represent imprecise concepts and properties, such as an object is *very big* or a situation is *highly dangerous*, as well as imprecise spatial information, such as two objects are *quite close* or there are *several* objects *near or inside* a restricted area.

Several proposals for the creation of fuzzy ontologies have emerged in the literature [2]. In fuzzy ontologies, concepts denote fuzzy sets and relations denote fuzzy relations; therefore, the axioms are not in general either true or false, but they may hold to some degree of truth. Correspondingly, fuzzy DLs are the extension of DLs to the fuzzy case; e.g., fuzzy $\mathcal{SROIQ}(\mathbf{D})$is the fuzzy extension of $\mathcal{SROIQ}(\mathbf{D})$–which roughly corresponds to the DL under OWL 2. Fuzzy inference engines, such as DeLorean [1] and FuzzyDL [5] support representing and reasoning with fuzzy ontologies. However, to date there is no fuzzy inference engine capable of managing and reasoning with fuzzy spatial knowledge.

In this paper, we identify three capabilities that should be incorporated to a fuzzy reasoner to support spatial reasoning for DIF.

Fuzzy spatial formal properties. Topological relations can be represented in the Region Connection Calculus (RCC), a formal theory describing a reduced set of spatial predicates and their properties; e.g. part, $\mathsf{disconnected}$ or $\mathsf{overlaps}$. Initial attempts for a fuzzy RCC have been described in the literature [12,14], but they have not been implemented in practice.

For example, a user should be able to add to a fuzzy ontology $\mathcal{O}$ a restriction in the type of vehicles allowed inside a restricted area as: $\langle \mathsf{AreaCompliance} \equiv (\textbf{not}\ \mathsf{Truck}) \sqcap \exists \mathsf{NTPP}.\mathsf{RestrictedArea}\rangle$, where NTPP is the RCC property non-tangential proper part. Then, a vehicle instance a might be classified as a member of the $\mathsf{AreaCompliance}$ with degree α given by a Best Degree Bound $\alpha = \mathsf{bdb}(\mathcal{O}, a : \mathsf{AreaCompliance})$ [2]. Different representations should be supported; e.g. following [14], the previous example would be: $\langle \mathsf{AreaCompliance} \equiv (\textbf{not}\ \mathsf{Truck}) \sqcap \exists(\mathsf{hasLocation}, \mathsf{hasAreaLocation}).\mathsf{NTPP}\rangle$, which means that: (i) a vehicle x has a location in a region r, (ii) there is a restricted area located in a region r', (iii) we impose that r is inside of r'.

Graded spatial properties. This includes spatial properties not included in the RCC, such as nearOf or $\mathsf{farFrom}$. These properties can have a fuzzy semantics (degree of closeness) but also a possibilistic one (degree of confidence in a binary relationship), as in [6,9]. Fuzzy spatial properties do not need to be defined in terms of the common membership functions (such as the trapezoidal), e.g.,

$$\langle (\mathsf{a}, \mathsf{b}) : \mathsf{nearOf} \geq \alpha \rangle, \alpha = \begin{cases} 1 & dist(a,b) \leq d_1 \\ 0 & dist(a,b) > d_1 + d_2 \\ \frac{d_1 + d_2 - dist(a,b)}{d_2} & otherwise\ (d_2 \neq 0) \end{cases}$$

These relations would be instantiated by geometrical calculations. This kind of calculations require a large amount of computations, since they must be executed in pair-wise entities. This necessarily calls for the implementation of optimized geometric models able to segment the space in influence zones in order to reduce the evaluation time of the functions.

It is also important to give a proper characterization of such properties in a graded ontology. Fuzzy extensions of OWL 2 [3] allow one to express that the properties are reflexive, symmetric, or transitive; this is not allowed for example in [14]. In particular, the propagation of fuzzy properties in transitive properties deserves some attention, as the choice of the fuzzy operators (in particular, of the fuzzy t-norm) has an impact. For example, assume that object o_1 is close to o_2 with degree 0.7 and that o_2 is close to o_3 with degree 0.7. Under the minimum t-norm, the closeness degree between o_1 and o_3 is at least 0.7; under the product, the closeness degree might be smaller (at least 0.49).

Spatial data aggregation. Situation assessments associated to spatial objects can be expressed in terms of fuzzy regions, that can be structured in layers. For example, we can derive a fuzzy region denoting danger around a restricted area based on the nearOf property of a vehicle (and other characteristics). Similarly, we can derive a second fuzzy region denoting danger associated to special traffic regulations in the surroundings, such as maximum speed. Combining these two spatial layers would give us the overall assessment of the situation. This could have many applications including security or risk evaluation. Although there has been some work to support aggregation operators in fuzzy ontologies [4], how to apply those or other operators to fuzzy regions is still an open issue.

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