A Fuzzy Logic Semantic Mapping Approach for Fuzzy Geospatial Ontologies

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Abstract*—The problem of finding semantic mappings between heterogeneous geospatial databases is a key issue in the development of a semantic interoperability approach. An essential step towards the success of a semantic approach is the ability to take into account the fuzzy nature of geospatial concepts being compared and of the semantic mapping process itself. While fuzzy ontologies and quantitative fuzzy matching methods have been proposed, they are not targeted at the geospatial domain. In this paper, we present a fuzzy semantic mapping approach for fuzzy geospatial ontologies, which employs fuzzy logics. The fuzzy semantic mapping approach has the capability to produce fuzzy qualitative semantic relations between concepts of fuzzy ontologies, which are richer than quantitative-only matches that are provided by existing approaches. In an application example, we show how fuzzy mappings can be used to propagate fuzzy queries to relevant sources of a network. In this way, the fuzzy semantic mapping supports geospatial data sharing among remote databases of the network while taking into account uncertainties that are inherent to the geospatial concepts and the semantic interoperability process.

Keywords-semantic interoperability; fuzzy logics; fuzzy geospatial ontology; semantic mapping

I. INTRODUCTION

The spreading of decentralized systems has created the need for approaches supporting users to find the relevant sources that can provide the data they required. Furthermore, an important number of users search for geospatial data, e.g. “flooding risk zones near built-up areas of Montreal.” Geospatial ontologies are considered as useful tools to support the identification of relevant geospatial data sources [1][2][3][4]. For example, Cruz et al. [5] indicate that the problem of querying geospatial databases in a distributed environment can be addressed by finding semantic mappings between the ontologies that describe each database.

However, several recent researches in GIScience have acknowledged the need for representing and dealing with the uncertainty and fuzziness of geospatial phenomena [6][7][8][9][10]. For example, a flooding risk zone is a fuzzy concept because different sources can define it with different characteristics.

Consequently, geospatial ontologies have to support the representation, but until now, the representation of fuzziness in ontologies has been mostly limited to the non-geospatial domain [11][12][13]. In addition, in order to resolve semantic heterogeneity among fuzzy geospatial ontologies, there is a need for a semantic mapping approach that will be able to deal with fuzzy geospatial ontologies.

We propose that fuzzy logic is well adapted for representing fuzzy knowledge about geospatial concepts, provided that the representation of concepts is explicit enough and takes into account all spatiotemporal aspects of concepts. In this paper, we propose a solution to the problem of fuzzy geospatial ontology and fuzzy semantic mapping. We first provide a definition of what is a fuzzy geospatial ontology. Then, we propose a new fuzzy semantic mapping approach, which takes as input the concepts of the fuzzy geospatial ontologies and finds semantic relations between concepts and their degree of fuzziness. The fuzzy semantic mapping approach integrates fuzzy logic operators and predicates to reason with fuzzy concepts. Finally, we demonstrate a possible application of the fuzzy semantic mapping, which is the propagation of fuzzy queries to the relevant sources of a network.

This paper is organized as follows. In Section 2, we discuss the role of fuzzy theory in semantic interoperability for GIS. In Section 3, we present the definition of the fuzzy geospatial ontology. In Section 4, we propose the fuzzy semantic mapping approach. In Section 5, we present the application for query propagation. In Section 6, we conclude this paper.

II. ROLE OF FUZZY THEORY IN SEMANTIC INTEROPERABILITY OF GEOSPATIAL DATA

Semantic interoperability is a major research topic to ensure data sharing among different geospatial databases in a network [14][15]. Semantic interoperability is the knowledge-level interoperability that provides cooperating databases with the ability to resolve semantic heterogeneities arising from differences in meanings of concepts [16]. Semantics, which is the meaning of expressions in a language [17] [18], is crucial for semantic interoperability because two systems can “understand” each other and share knowledge only if they make the meaning of their concepts apparent to each other. Ontologies, which are explicit specifications of a conceptualisation [19], aim at capturing semantics of data [20] [21][22] [14][23] [24]. Ontologies with poor (implicit) semantics provide weaker interoperability while ontologies with strong semantics based on logical theory support richer semantic interoperability

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[25]. On the other hand, uncertainty in the semantics of concepts should be considered as a kind of knowledge that must also be explicit in conceptual representations, as argued by Couclecis [7]. Fuzzy logic proposed by Zadeh is considered in GIScience as a suitable way to represent uncertain knowledge and reason with it. Therefore, several approaches have proposed to augment ontologies with fuzziness, for example for news summarization [11], for information retrieval in the medical domain [12], or for image interpretation [13]. However, these approaches are not targeted at the geospatial domain. For example, geospatial concepts are often described with properties (e.g., “inclination” of “lowland”), which range of values can be fuzzy. However, existing fuzzy ontology representations and ontology mapping approaches do not consider properties with fuzzy range of values. Other approaches in the geospatial domain use fuzzy sets to assess similarity of categorical maps [26]. But this approach is not general and aims at categorical maps, while we argue that a more general framework for any geospatial fuzzy ontology is needed. In addition, we argue that quantitative fuzzy similarity have limited expressivity in comparison to qualitative semantic relations, which are easier to interpret by users. To our knowledge, there is no existing fuzzy semantic mapping approach that produces fuzzy semantic relations. In our paper, we propose a definition of the fuzzy geospatial ontology, and an approach that addresses this need.

III. Fuzzy geospatial ontology

An ontology is usually defined as a set of concepts (or classes) that represent entities of the domain of discourse, relations and/or properties, and axioms that indicate statements that are true within that domain of discourse [14]. An example of axiom is “all intersections involve at least two roads.” We follow a similar approach to define the fuzzy geospatial ontology. However, in the fuzzy ontology, we consider that membership of a property or relation in the definition of a concept can be quantified. In a crisp ontology, the membership degree of a property of relation into the definition of a concept is always one or zero. This means that either a concept has that property; or it does not have it. In the fuzzy ontology, this membership degree varies between zero and one, to indicate partial membership. Therefore, in a fuzzy ontology, concepts do not have a fully determined definition.

We define the fuzzy geospatial ontology as a 5-tuple: $O = \{C, R, P, D, rel, prop\}$, where C is a set of concepts, which are abstractions of entities of the domain of discourse; R is a set of relations; P is a set of properties for concepts; D is a set of possible values for properties in P, called range of properties; rel: $[R \rightarrow C \times C] \rightarrow [0, 1]$ is a fuzzy function that specifies the fuzzy relation that holds between two concepts; prop: $[P \rightarrow C \times D] \rightarrow [0, 1]$ is a fuzzy function that specifies the fuzzy relation between a concept and a subset of D. D is therefore a fuzzy range of values. The set of relations R includes relations such as “has geometry,” which indicates the geometry of instances of the concept, such as polygon, moving polygon, line, and other GML spatial and spatiotemporal types. It also includes spatial relations such as “Is_located_at,” which indicates the location of an instance of the concept, and other topological, directional and orientation spatial relations. An example of fuzzy property “inclination” of the fuzzy concept “lowland” is given on Fig. 1. Lowlands are regions which inclination is relatively flat, but there is a certain level of fuzziness when we try to determine if a given region is a “lowland.” While the value “flat” of the “inclination” property has the fuzzy membership of 0.8 to the range of values of “inclination,” the value “low” has a lower membership value of 0.10. This reflects the fact that a greater percentage of lands with flat inclination are considered as members of the geographical category “lowland,’ in comparison to lands with “low” inclination.

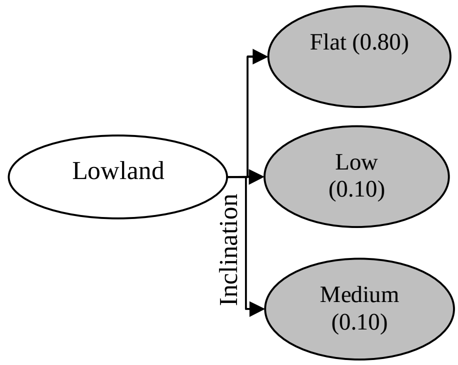


Figure 1. Example of fuzzy property “inclination” for concept “lowland”

For the purpose of our approach, we define a concept with a conjunction of a set of axioms A_C, where each axiom is a fuzzy relation or property that defines the concept:

$$C = A_1 \sqcap A_2 \sqcap \ldots \sqcap A_n.$$

We use the term axiom, which is usually employed to refer to the whole expression that defines a concept, because a concept could also be defined by one feature (property or relation).

IV. Fuzzy semantic mapping process

In this section, we propose the new fuzzy semantic mapping approach. The idea of this approach is to use fuzzy logics to first determine the fuzzy inclusion of a concept into another concept from a different ontology, based on the fuzzy inclusion of each axiom of the first concept into axioms of the second concept. Then, fuzzy predicates, which value depends on the fuzzy inclusion, are used to infer the semantic relation between the two concepts.

Let two concepts C and C’, defined as follows:

$$C = A_1 \sqcap A_2 \sqcap \ldots \sqcap A_n$$

$$C' = A_1' \sqcap A_2' \sqcap \ldots \sqcap A_m'$$

We define the fuzzy semantic mapping between C and C' as follows:

Definition (fuzzy semantic mapping) A fuzzy semantic mapping m^C between *C* and *C*' is a tuple m^C = <*C*, *C'*, *rel*(*C*, *C*'), μ(*C*, *C*')>, where *rel* is a semantic relation between *C* and *C*', and μ(*C*, *C*') is the fuzzy inclusion of *C* into *C*'.

First, we explain how the fuzzy inclusion of *C* into *C*' is computed. Secondly, we explain how the semantic relation *rel* between *C* and *C*' is determined.

A. Fuzzy inclusion

We define the fuzzy inclusion as the membership degree of a concept in another. This means that when the value of the fuzzy inclusion is 1, the first concept is entirely included in the second concept; when it is zero, no axiom of the first concept intersects with axioms of the second. The fuzzy inclusion of C into C' is denoted with μ(C, C') :

$$\mu(C,C') = \frac{\sum_{A \in (A_1,\ldots,A_n,A'_1,\ldots A'_m)} \min(\mu_C(A), \mu_{C'}(A))}{\sum_{A \in (A_1,\ldots,A_n,A'_1,\ldots A'_m)} \mu_C(A)}, \quad (1)$$

where $\mu_C(A)$ is the membership degree of axiom A in concept C. We know that this membership degree comes from the definition of the concept in the fuzzy geospatial ontology. Let A: <r.D> and A': <r'.D'> be two axioms, where D and D' are fuzzy domains. For example, <shape.((0.2, circle);(0.8, ellipse))> represents the fuzzy relation on Fig. 1.

To compute (1), which relies on the membership of axiom A in concept C', and where axiom A of concept C might not be already in the definition of the concept C', we need the membership of axiom A in axiom A' of C'. The membership degree of A into A' is determined by the Zadeh conjunction for fuzzy sets:

$$\mu(A,A') = \min(\mu(D,D'), \mu(r,r')) . \quad (2)$$

The function μ(X1, X2) over any fuzzy sets X1, X2 is defined as follows, using the fuzzy implication principle of fuzzy logics [27]:

$$\mu(X1,X2) = \inf_{x \in X1 \cup X2} (\mu_{X1}(x) \Rightarrow_f \mu_{X2}(x)), \quad (3)$$

where $\Rightarrow_f$ is a fuzzy implication operator from [0,1] into [0,1]. There are several definitions for the fuzzy implication operator (including Gödel, Gogen and Lukasiewicz fuzzy implications, see Bosc and Pivert [27]). We use Lukasiewicz fuzzy implication because of its superior flexibility, which is defined as follow:

$$\mu_{X1}(x) \Rightarrow_L \mu_{X2}(x) = \begin{cases} 1 & \text{if } \mu_{X1}(x) \le \mu_{X2}(x) \\ 1-\mu_{X1}(x)+\mu_{X2}(x) & \text{otherwise} \end{cases} . \quad (4)$$

To compute μ(D, D') with (3), we use the Lukasiewicz fuzzy composition operator, denoted with the symbol ⊗, and which determines the membership of a first element ε_i' in a set D, knowing the membership degree of ε_i' in ε_j and the membership degree of ε_j in D (Fig. 2). The symbol ε is used to indicate an element of the range of values of a property or a relation of the fuzzy geospatial ontology.

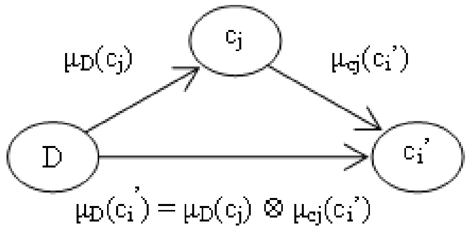


Figure 2. Fuzzy composition principle

The membership degree of ε_i' in D writes as:

$$\mu_D(\varepsilon_i') = \sum_j \mu_D(\varepsilon_j) \otimes \mu_{\varepsilon_j}(\varepsilon_i'), \ \forall j \middle| (\neg\varepsilon_j \perp \varepsilon_i), \quad (5)$$

where

$$\mu_D(c_j) \otimes_L \mu_{c_j}(c_i') = \max(\mu_D(c_j) + \mu_{c_j}(c_i') - 1, 0), \quad (6)$$

according to Lukasiewicz's definition of the fuzzy composition operator.

To determine $\mu_{\varepsilon j}(\varepsilon_i')$, which is the membership degree of an element ε_i' of a range of values in an element ε_j of another range of values, we have developed a fuzzy membership degree measure. This measure is based on the relative position of ε_j and ε_i' in an upper-level ontology O. An appropriated ontology for this task would be a domain-independent, largely recognized lexical base, such as WordNet. However, other more specialized upper-level ontologies might be more useful, depending on the domain of application. Let $<_O$ be a hierarchical, is-a relationship between terms in O, such that t $<_O$ t' means that t is more specific (less general) than t'. Let P(ε_j, ε_i') be the path relating ε_j to ε_i' in O, according to this hierarchy: P(ε_j, ε_i') = {ε_j, t1, t2, … ε_i'} so that t1, t2, … is the ordered set of nodes from ε_j to ε_i' in O. Let d(t_k) the set of descendants of a node in O. We define $\mu_{\varepsilon j}(\varepsilon_i')$ as follows:

$$\mu_{\varepsilon_j}(\varepsilon_i') = \begin{cases} 1 & \text{if } \varepsilon_i \prec \varepsilon_j \\ \dfrac{1}{\prod_{\forall t_k \in P(\varepsilon_j, \varepsilon_i')} |d(t_k)|} & \text{if } \varepsilon_i' > \varepsilon_j \\ 0 & else \end{cases} . \qquad (7)$$

This equation means that, when ε_i' is more specific than ε_j, it is entirely included in ε_j, and when ε_i' is more general than ε_j, $\mu_{\varepsilon j}(\varepsilon_i')$ decreases with the number of descendants of its subsumers. Replacing results of (7) in (6), we obtain the membership of each element of the fuzzy range D' in D, which, in turn, allows to determine μ(D, D') with (3). Eq. (7) is also used to determine μ(r, r'), so these results can be replaced in (3).

From the fuzzy inclusion given in (2), we obtain the semantic relation between the axioms, rel(A, A'), using the following rules, which are derived from the fuzzy set relationship definitions:

(R1) A ≡ A' ⇔ μ(A, A') =1 ∧ μ(A', A) =1

(R2) A ⊑ A' ⇔ μ(A, A') =1 ∧ μ(A', A) <1

(R3) A ⊒ A' ⇔ μ(A, A') <1 ∧ μ(A', A) =1

(R4) A ⊓ A' ⇔ 0 < μ(A, A') <1 ∧ 0 < μ(A', A) <1

(R5) A ⊥ A' ⇔ μ(A, A') =0 ∧ μ(A', A) =0.

B. Semantic relation

In order to determine the semantic relation between concepts, we have defined a set of predicates. The semantic relation between two concepts is determined by the following expression:

$$rel(C,C') = I(A_C, A_{C'}) \otimes_{\mathrm{Pr}} C(A_C, A_{C'}) \otimes_{\mathrm{Pr}} CI(A_C, A_{C'}),$$

where $I(A_C, A_{C'})$, $C(A_C, A_{C'})$ and $CI(A_C, A_{C'})$ are three predicates that respectively evaluate the intersection of axioms of the concept *C* with axioms of *C'*, the inclusion of axioms of *C'* in axioms of *C*, and the inclusion of axioms of *C* in axioms of *C'*. We have defined a composition operator, denoted $\otimes_{\mathrm{Pr}}$, the function of which is to give the semantic relation between *C* and *C*', based on the value of those three predicates. The composition operator takes as input the value for the three predicates for *C* and *C*', and returns the semantic relation between *C* and *C*'.

For any predicate *Pr*, the possible values of *Pr* are:

- *B* value, if for all axioms of *C* there is an axiom of *C'* that verifies predicate *Pr*, and vice-versa. For example, $I(A_C, A_{C'}) = B$ if for all axioms in A_C, there is an axiom in $A_{C'}$ that intersects this axiom (as determined by rules R1 to R5 defined in the previous section), and vice-versa;
- *S* value, if there exist some axioms of *C* and axioms of *C'* that verify predicate *Pr*, but not all;
- *N* value, if there exists no axiom of *C* and *C'* that verifies predicate *Pr*.

These principles for determining the value of a predicate are formalized as follows (where logic symbols are ∀(for all), ∃ (there exists) ⊥ (disjoint) and ¬ (negation):

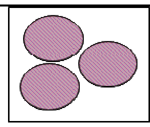
$$I(C,C') = \begin{cases} B & \forall i \exists j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \wedge \\ & \exists i \forall j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \\ S & \exists i \exists j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \wedge \\ & \neg[\forall i \exists j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \wedge \\ & \exists i \forall j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0)] \\ N & \neg \exists i \exists j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \end{cases}$$

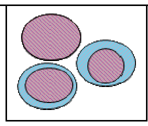
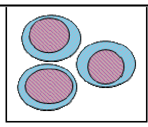
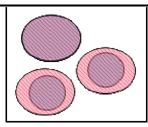
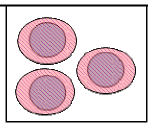
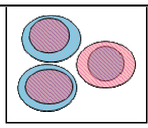
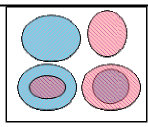
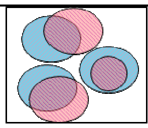
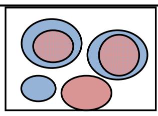
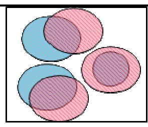
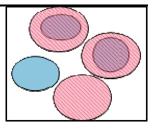
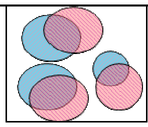
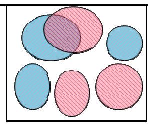
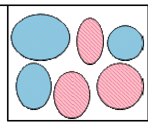
$$C(C,C') = \begin{cases} B & \forall i \exists j, rel(A_i, A_j') \in \{\equiv, \sqsupseteq\} \wedge \mu(A_i, A_j') \neq 0 \\ S & \exists i \exists j, rel(A_i, A_j') \in \{\equiv, \sqsupseteq\} \wedge \mu(A_i, A_j') \neq 0 \wedge \\ & \neg \forall i \exists j, rel(A_i, A_j') \in \{\equiv, \sqsupseteq\} \wedge \mu(A_i, A_j') \neq 0 \\ N & \neg \exists i \exists j, rel(A_i, A_j') \in \{\equiv, \sqsupseteq\} \wedge \mu(A_i, A_j') \neq 0 \end{cases}$$

$$CI(C,C') = \begin{cases} B & \forall i \exists j, rel(A_i, A_j') \in \{\equiv, \sqsubseteq\} \wedge \mu(A_i, A_j') \neq 0 \\ S & \exists i \exists j, rel(A_i, A_j') \in \{\equiv, \sqsubseteq\} \wedge \mu(A_i, A_j') \neq 0 \wedge \\ & \neg \forall i \exists j, rel(A_i, A_j') \in \{\equiv, \sqsubseteq\} \wedge \mu(A_i, A_j') \neq 0 \\ N & \neg \exists i \exists j, rel(A_i, A_j') \in \{\equiv, \sqsubseteq\} \wedge \mu(A_i, A_j') \neq 0 \end{cases}$$

For *C* and *C'*, the domain of quantifiers is respectively $i \in \{1,\ldots, n\}$ and $j \in \{1,\ldots, m\}$. When the three predicates are evaluated within {B, S, N}, the result is 14 classes of cases, which are provided in Table 1. This table defines the $\otimes_{\mathrm{Pr}}$ operator: each combination of values for the three predicates is associated with a resulting semantic relation. For example, *C* (semantically) contains *C'* if $I(A_C, A_{C'}) = B$, $C(A_C, A_{C'}) = B$ and $CI(A_C, A_{C'}) = S$ (second line of Table 1). In the associated illustrations, blue sets represent axioms of *C*, and red sets axioms of *C'*.

TABLE I. SEMANTIC RELATIONS IN FUNCTION OF THE COMBINATION OF PREDICATE VALUES ($\otimes_{\mathrm{Pr}}$ OPERATOR)

Semantic relationship	Value of $I(A_C, A_{C'})$	Value of $C(A_C, A_{C'})$	Value of $CI(A_C, A_{C'})$	Representation
1. Equivalence	B	B	B	

2. Contains	B	B	S	
	B	B	N	
3. Contained In	B	S	B	
	B	N	B	
4. Partial S-Containment (S=Symetric)	B	S	S	
	S	S	S	
5. Partial L-Containment (L-LEFT)	B	S	N	
	S	S	N	
6. Partial R-containment (R=RIGHT)	B	N	S	
	S	N	S	
7. Strong Overlap	B	N	N	
8. Weak Overlap	S	N	N	
9. Disjoint	N	N	N	

Once the semantic relations and fuzzy inclusion are determined between concepts, we aim to show that this information can be used to find relevant sources of a network through propagation of query.

V. APPLICATION EXAMPLE

The presented application aims to demonstrate the usefulness of the proposed approach. As an example of fuzzy ontologies, we consider the ontology fragments in Fig. 3 and Fig. 4.

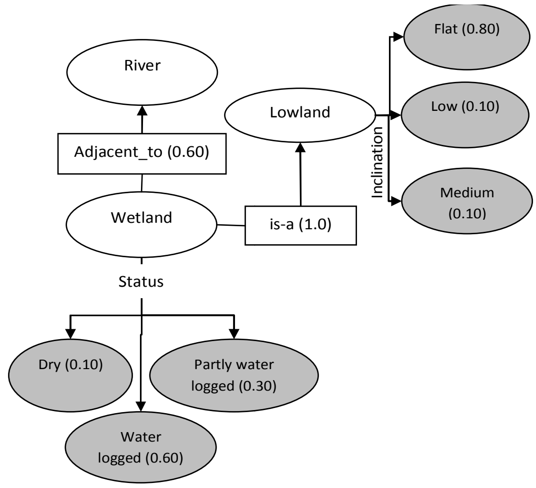


Figure 3. Portions of ontology A for the application example

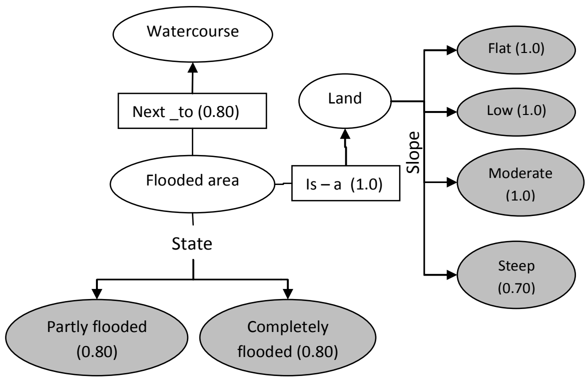


Figure 4. Portions of ontology B for the application example

The fuzzy ontology A describes the concept "wetland" as "lowland" which can have flat, low or medium slope. The values "flat," "low" and "medium" constitute the range of the property "has slope." For each of these values, there is a fuzzy membership value that indicates the degree of membership of the value into the range of the property. Similarly, the wetland has the property "status," which range is composed of values "dry," "partly waterlogged" and "waterlogged."

The fuzzy ontology B describes the concept "flooded area," which has the property "state" with values "partly flooded" and "completely flooded."

Consider that the user of ontology A needs to find data on wetlands in a given region. To do so, the ontological description of concept "wetland" is compared to the ontological description of concepts from other available sources, for instance fuzzy ontology B. The fuzzy matching approach is used for this purpose. The following shows the values that are obtained for the membership of axioms of both ontologies into the concepts of "flooded area" and concept of "wetland:"

$\mu_{flooded\_area}$(<is_a.lowland>) = 0.50

$\mu_{wetland}$(<is_a.lowland>) = 1.00

$\mu_{flooded\_area}$(<adjacent_to.river>) = 0.30
$\mu_{wetland}$(<adjacent_to.river>) = 0.60

$\mu_{flooded\_area}$(<status.dry>) = 0.00
$\mu_{wetland}$(<status.dry>) = 0.10

$\mu_{flooded\_area}$(<status.partly_waterlogged>) = 0.10
$\mu_{wetland}$(<status.partly_waterlogged >) = 0.30

$\mu_{flooded\_area}$(<status.waterlogged>) = 0.20
$\mu_{wetland}$(<status.waterlogged >) = 0.60

$\mu_{flooded\_area}$(<is_a.land>) = 1.00
$\mu_{wetland}$(<is_a.land>) = 0.50

$\mu_{flooded\_area}$(<next_to.watercourse>) = 0.80
$\mu_{wetland}$(<next_to.watercourse>) = 0.30

$\mu_{flooded\_area}$(<state.partly_flooded>) = 0.80
$\mu_{wetland}$(<state.partly_flooded>) = 0.10

$\mu_{flooded\_area}$(<state.completely_flooded>) = 0.80
$\mu_{wetland}$(<state.completely_flooded >) = 0.20

When those values are inserted in (1), we obtain that μ(flooded_area, wetland) = 0.69.

The semantic relation between "wetland" and "flooded area" is obtained by computing the three predicates, which values are the following:

$I(A_{flooded\_area}, A_{wetland}) = B$
$C(A_{flooded\_area}, A_{wetland}) = S$
$CI(A_{flooded\_area}, A_{wetland}) = N$

The resulting semantic relation, according to Table 1, is "partial left containment," which means that some axioms in the definition of "wetland" are included in some axioms of "flooded area." The fuzziness of this relation is 0.69.

When the requestor receives a set of concepts that partly matches its query, he or she can select the more relevant concept using two complementary information elements, the semantic relation and the degree of fuzziness of this relation. The fuzziness is more than a semantic similarity, since it takes into account the fuzziness of concepts being compared. For example, a property value which has a low membership degree into the concept's definition, such as "dry" in the above example, will have less "weight" in the computation of the semantic mapping than a property that has higher membership degree, such as "waterlogged."

While the objective of the paper was not to demonstrate the cost of implementing the approach, we note that the concept of fuzzy mapping can be useful to support various semantic interoperability tasks. More particularly, it is an approach that can support query propagation in decentralized environment. In such environment, there is no central authority that can identify the sources that can process a query. Therefore, the goal of query propagation is to forward the query from source to source through an optimal path, i.e. a path that will contain the most relevant sources with respect to the query. The qualitative and quantitative mappings issued by the fuzzy semantic mapping algorithm can be used as criteria to select the sources that are relevant along the path, while taking into account the fuzziness of semantic mappings.

VI. CONCLUSION

In the geospatial domain, it is essential to consider the uncertainty and fuzziness of geospatial phenomena. Establishing semantic mappings between fuzzy geospatial ontologies is still an issue that was not fully addressed. In this paper, we have dealt with some problems related to the representation of fuzziness in geospatial ontologies, and fuzzy semantic mapping between fuzzy geospatial ontologies. In order to address these problems, we have proposed a fuzzy geospatial ontology model, and a new fuzzy semantic mapping approach. The determination of fuzzy semantic mappings is based on fuzzy logics and a set of predicates that were defined to determine fuzzy semantic relations between concepts, which are complementary to the fuzzy inclusion degree between concepts. The qualitative and quantitative results give more information for the user to understand the nature of relation between its fuzzy query and available concepts. One of the possible uses of our approach is query propagation in a network of heterogeneous, fuzzy geospatial ontologies. Query propagation determines to which nodes of a network a given query should be forwarded in order to obtain optimal query results. Query propagation provides the user with a path in the network that contains the most relevant sources to answer the query. In future work, we will apply this approach to the issue of query propagation. We also plan to extend the fuzzy semantic mapping approach to more complex cases of the fuzzy spatial, temporal and spatiotemporal features of concepts. This is essential for propagating queries to relevant concepts, for if spatiotemporal properties have different meanings, the query may return inaccurate results. In addition, we plan to extend the approach to the case of an ad hoc network, where sources could be added or removed from the network in real time.

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