Similarity-Based Retrieval for Geospatial Semantic Web Services Specified using the Web Service Modeling Language (WSML-Core)

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Abstract. What prevents the geospatial semantic web from taking off is not a missing architecture and protocol stack but, beside other aspects, the question of how web services can be semi-automatically discovered and whether and to what degree they satisfy user requirements. Two approaches turned out to be useful for semantic-enabled geospatial information retrieval: subsumption reasoning and similarity measurement. However, while the former one can be applied to query service ontologies described in OWL-S or WSMO/WSML, most existing similarity theories are not able to cope with logic-based service descriptions. This paper presents initial results on developing a directed and context-aware similarity measure that compares WSML concept descriptions for overlap and therefore supports retrieval within the upcoming geospatial semantic web.

1 Introduction & Motivation

The idea of the web service oriented architecture (SOA) is based on the publish-find-bind pattern. To make a service available on the Internet, the provider has to *publish* relevant metadata to a service broker. Next, a requestor can discover (*find*) registered services and establish a connection (*bind*) to them. From a syntactical point of view the SOA-Stack offers specifications for each part of the pattern: WSDL for web service description, UDDI as a repository for description, discovery and integration and SOAP as protocol for service binding. However, to enable semi-automatic service discovery, i.e. to specify the capabilities of web services and search queries in an unambiguous and computer-interpretable way, a semantic-enabled markup language becomes necessary. Moreover, beside this common language, a framework needs to be defined specifying which mandatory and optional metadata should be annotated. From the provider's perspective, service ontologies described using OWL-S [1] or WSMO [2] satisfy these requirements[1]. Both define functional and non-functional service properties, service grounding (binding) and a semantic-enabled annotation

[1] A detailed comparison between both approaches is discussed in [3]; note however that it is written from the perspective of the WSMO community.

language. Although they specify *what* has to be said about a service, the definition of a semantic web adequate search paradigm is out of their scope.

Over the last years of research, subsumption reasoning and similarity measurement turned out to be applicable for geospatial information retrieval. The idea behind subsumption-based retrieval as described by Lutz & Klien [4] is to rearrange a queried application ontology taking a search concept into account and to return a new taxonomy in which all subconcepts of the injected search phrase satisfy the user's requirements. However, using this approach forces the user to ensure that the search concept is specified in a way that it is neither too generic (and therefore at a top level of the new hierarchy) nor too specific to get a sufficient result set. In fact the search concept is a formal description of the minimum characteristics all retrieved concepts need to share. Moreover no measurement structure is provided answering the question of *which* of the returned concepts fits best. However, this is not necessarily a critical point because all subconcepts at least share the requested properties. In contrast, similarity computes the degree of overlap between search and compared-to concepts and, as measurement structure, provides a (weak) order. Both characteristics turn out to be useful for information retrieval and matching scenarios: on the one hand the determination of conceptual overlap simplifies phrasing an adequate search concept and on the other hand the results are ordered by their degree of similarity to the *searched* concept. Similarity-based retrieval does not necessarily imply a subsumption relation between search and compared-to concepts (see Figure 1), in some cases even disjoint concepts may be similar to each other (e.g. Mother, Father). In contrast to subsumption-based retrieval, the search phrase typed into the system is not an artificial construct, but the concept the user is really looking for in the external service ontology without presuming that all returned concepts share a specific property.

In other words, the benefits similarity offers during information retrieval, i.e. to deliver a flexible degree of conceptual overlap to a searched concept, stand against shortcomings during the usage of the retrieved information, namely that the results do not *necessarily* fit the user's requirements. To make the difference between both approaches more evident, one could imagine a search phrase specified using a shared vocabulary (see Figure 1) to retrieve all concepts whose instances *overlap* with waterways. In contrast to the subsumption-based approach, similarity measurement would additionally deliver concepts whose instances are located *inside* and *adjacent* to waterways, and indicate through a lesser degree of similarity that these concepts are close to, but not identical with the user's intended concept.

Following the above argumentation, similarity supports users during information retrieval; however this presumes that the chosen similarity measure supports the representation language of the inspected service (ontology). It turns out that, besides the fact that several similarity theories make fundamentally different assumptions about *how* and *what* is measured (e.g. feature vs. geometric model [5]), most of them come with their own proprietary knowledge representation format. In contrast, the majority of service ontologies are specified using standardized or commonly agreed upon logic-based knowledge representation languages and especially various kinds of description logics. This leads to a gap between available similarity theories and existing ontologies which oppose a wider application of similarity measures as part of the geospatial semantic web.

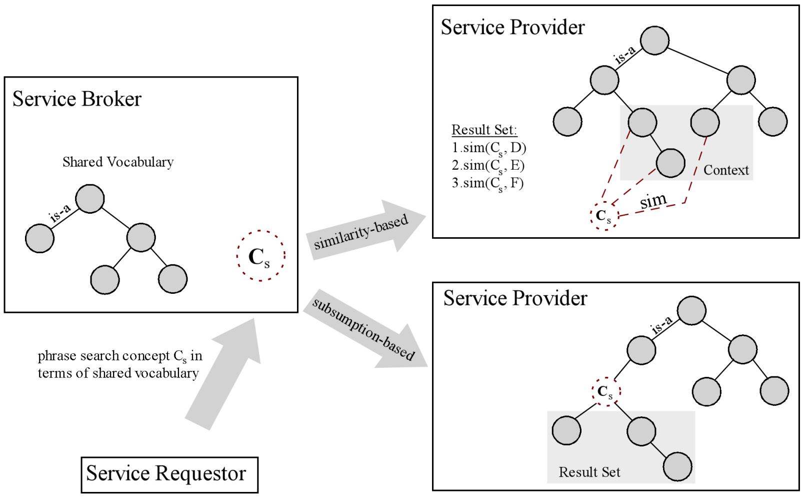

Figure 1. Subsumption and similarity-based retrieval using a shared vocabulary

Additionally, most proprietary knowledge representation formats associated with existing similarity theories lack a formal semantics and also language constructs proven to be useful for conceptualization (such as role-filler pairs). This is a crucial point because in computer science the concepts between which similarity is measured are *representations* of the concepts in our minds. Consequently, the lack of a precise and expressive representation language has impact on the quality of the resulting similarity assessments as discussed in [6] for the feature-based MDSM theory [7]. The same arguments hold for geometric approaches to similarity based on Gärdenfors' idea of conceptual spaces [8]. To integrate relations and hence improve the expressivity of conceptual spaces for similarity measures, Schwering [9] for instance combines the geometric approach with classical network models. Initial approaches towards similarity measures for expressive description logics are discussed in [10, 11]. A theory applying similarity for web service comparison based on OWL-S is presented in [12]; however it does not take neighborhood models into account. An overview about existing similarity theories, their application areas and characteristics, is out of the scope of this paper and was recently discussed in [5].

This paper presents initial results on how a similarity theory comparing conceptualizations specified in the web service modeling language (WSML) can support semi-automatic information retrieval and matching tasks within the upcoming geospatial semantic web.

2 Similarity between WSML Concept Descriptions

This section gives a brief introduction into the web service modeling language WSML, followed by a service integration scenario. Next, the similarity theory and its formal aspects are discussed in detail.

2.1 WSMO and WSML

Based on the web service modeling framework (WSMF) developed by Fensel and Bussler [13], WSMO [2] specifies four main modeling elements describing various aspects of semantic web services needed within the publish-find-bind pattern, but also for service chaining (orchestration).

- **Ontologies** providing the formal semantics for goals, web services and mediators and linking human and machine terminology together.
- **Goals** specifying the user's aims with respect to the requested service functionalities
- **Web services** representing the offered functionality in terms of its capabilities and non-functional properties.
- **Mediators** offering several types of mediators to overcome interoperability problems.

WSML [14] is the corresponding modeling language providing a formal syntax and semantics to describe these elements in a machine-interpretable and unambiguous way. It supports both a condensed machine oriented as well as a human readable syntax and comes in five flavors of different expressivity: WSML-Core, WSML-DL, WSML-Flight, WSML-Rule and WSML-Full. For more details about these variants see [14; section 3-9]. Independent from a certain language variant the WSML ontology specifications distinguish between the following elements: concepts (and their attributes), relations, instances (of concepts and relations) and axioms. However, the abilities to describe them depend on the chosen WMSL flavor. For each element, additional non-functional properties (nfp), mostly taken from the Dublin Core schema (such as a plain text description) can be specified.

The presented similarity measure is defined to cope with the expressivity of WSML-Core; therefore this section gives a broad insight into its abilities and restrictions (see Figure 2). WSML-Core is based on the intersection of description logics with logic programming and acts as a base and exchange vocabulary for WSMO. The usage of relations is restricted to binary predicates and cardinality restrictions are not supported. The WSML documentation recommends using concept attributes instead of relations wherever possible. Moreover WSML-Core does not allow specifying the attribute features *transitive*, *symmetric*, *reflexive* and *inverseOf* within local concept descriptions. However, they can be added as global axioms to the service ontology and linked to the intended concept via the Dublin Core element *dc:relation* [14; p. 27]. Although WSML distinguishes between constraining (*ofType*) and inferring (*impliesType*) attribute and relation descriptions, the former can only be applied to datatypes within the Core variant [14; p. 17]. WSML offers built-in datatypes, such as strings, integers, doubles or dates which correspond to XML Schema datatypes and operators (XQuery functions) such as *equal* or *numericGreaterThan*. The syntax and semantics (mapped to Horn Logic) of the language constructs used within WSML-Core as well as an exemplary concept definition are depicted in Figure 2. Please consult the WSML documentation [14; p. 27-30] for more details.

WSML-Core (syntax)	Horn Logic (semantics)
π(*head* **impliedBy** *body*.)	$\pi(head) \leftarrow \pi(body)$
π(*lexpr* **or** *rexpr*)	$\pi(lexpr) \vee \pi(rexpr)$
π(*lexpr* **and** *rexpr*)	$\pi(lexpr) \wedge \pi(rexpr)$
π(*X1* **memberOf** *id2*)	$id2(X1)$
π(*id1* **subConceptOf** *id2*)	$id2(x) \leftarrow id1(x)$
π(*X1*[*id2* **hasValue** *X2*])	$id2(X1,X2)$
π(*id1*[*id2* **impliesType** *id3*])	$id3(y) \leftarrow id1(x) \wedge id2(x,y)$
π(*id1*[*id2* **ofType** *dt*])	$dt(y) \leftarrow id1(x) \wedge id2(x,y)$
$\pi(p(X_1,\ldots,X_n))$	$p(X_1,\ldots,X_n)$

```
concept Youth_Hostel subConceptOf {Housing, Building}
    nonFunctionalProperties
        dc#description hasValue "concept of a youth hostel"
    endNonFunctionalProperties
    category ofType _integer
    service impliesType SelfService
    offers impliesType Room
    ...
```

Figure 2. Syntax and Semantics of WSML-Core

Although, we stick to the human readable syntax within this paper, it has to be mentioned that compared WSML descriptions have to be preprocessed before similarity is measured. The necessary steps are described in [14; p.42f] and result in a WSML normal form (see also [11]). The underlying idea is to decompose complex descriptions to simple ones. For instance the head of the concept Youth_Hostel in Figure 2 is expanded to: *concept* Youth_Hostel *subConceptOf* Housing and *concept* Youth_Hostel *subConceptOf* Building. Note that concepts inherit all attributes specified for their ancestors.

2.2 Scenario

This section specifies a simplified integration scenario to illustrate the presented similarity theory. We assume that a European lodging portal on the Internet is providing information about accommodations in cities attractive to tourists. To avoid maintenance costs, the service provider does not store the information in a local database, but dynamically connects to external (geo) web services. However, to offer a consistent interface and vocabulary to the portal users, the service provides its own terminology. To do so, the types of accommodations distinguished in the external services have to be aligned to the local terminology. One of the external services, delivering information about accommodations in Amsterdam, provides separate conceptualizations for houseboats and botels[2] while the local knowledgebase does not make this distinction. The task of similarity measurement within this scenario is to propose whether botels should be displayed as houseboats, hotels or youth hostels (see Figure 2 and Table 1) within the local terminology presented to the system user. The provider therefore runs a similarity query using the external concept *Botel* as search phrase (C_s) to be compared to the local conceptualizations. In addition, the service provider can specify a search context, i.e. a description of the minimum requirements all compared-to concepts need to fulfill (to be housings in this case). See section 2.3 for details on context and its impact on measured similarity.

[2] For instance: Hotel Amstel Botel Amsterdam: http://www.amstelbotel.nl/

Botel	Houseboat	Hotel
subConceptOf {Boat, Housing}	**subConceptOf** {Boat, Housing}	**subConceptOf** {Building, Housing}
category **ofType** _integer		
service **impliesType** Service	category **ofType** _string	category **ofType** _integer
offers **impliesType** Room	service **impliesType** SelfService	service **impliesType** Service
borders(i)[3] **impliesType** Waterway	inside **impliesType** Waterway	offers **impliesType** Room

Table 1. Conceptualizations for the Botel-Houseboat scenario

Both the external service and the accommodation portal stick to a common vocabulary. For reasons of simplicity it is assumed that all concepts and attributes except Botel, Houseboat, Hotel and Youth_Hostel are defined within this shared vocabulary.

2.3 Similarity Measurement between WSML-Core Concept Descriptions

The presented theory measures similarity between concepts (in normal form) by stepwise comparing their WSML-Core descriptions, where a high level of overlap indicates high similarity and vice versa. To do so, all language constructors available to define concepts in WSML-Core, i.e. *subConceptOf* and *attribute* (respectively *relation*) as well as the restrictions for their fillers by *typeOf* and *impliesType*, have to be taken into account. Similarity is therefore defined as a polymorphic, binary and real-valued function $\mathbf{X} \times \mathbf{Y} \rightarrow \mathbb{R}[0,1]$ providing implementations for all language constructs. The overall similarity (sim_o) between concepts is just the normalized (and weighted) sum of the single similarities calculated for all parts of the concept descriptions. A similarity value of 1 indicates that compared concept descriptions are equal, whereas 0 implies total dissimilarity. In the following σ denotes the normalization factor while ω is used to represent weightings.

First of all, it has to be determined which parts of the concept descriptions are compared to each other. To do so, the similarity for each element from the Cartesian product $X \times Y$ for a certain constructor is measured. From the resulting set of tuples, those with the highest similarity value are chosen for further computation; where each element is only selected once. In other words, for *each* part of the search concept's description, a counterpart from the compared-to concept's description is chosen in a way that the most similar parts are compared and each part is only examined once. The sets of these selected pairs are called S_c (selected primitive concepts), S_{ac} (selected attributes with concept fillers) and S_{ad} (selected attributes with datatype fillers) within this paper.

The presented similarity theory is directed, i.e. asymmetric [7], in a sense that the resulting overall similarity depends on the search direction. Therefore $sim_o(C, D)$ is not necessarily equal to $sim_o(D, C)$. While each element of the search concept's description is compared to an element from the compared-to concept, some parts of

[3] Note that *borders(i)* (borders from inside) corresponds to TPP and *inside* to NTTP in RCC8 [15]; however these relations need more investigation for 3D spatial neighborhoods [16].

the latter may remain outside of S_c and S_a. This is always the case if the compared-to concept is specified by more elements than the search concept. The similarity value for these remaining parts is always 0 while they do not increase the normalization factor σ. If however the search concept is described by more elements than can be compared, σ is increased by 1 for each remaining part. As a result the overall similarity is decreased. In other words, if the examined concept in the service provider's ontology is more specific than requested by the user (via the search concept) this has no impact on the measured overall similarity. On the other side, similarity decreases if the user's search concept is more specific than its counterpart in the service ontology.

In Figure 1 as well as in section 2.2 context is defined as a component of similarity-based retrieval. The idea of context (see also MDSM [7]) is on the one hand to determine which parts from the service ontology have to be compared to the search concept and on the other hand to influence the measured similarity making it situation-aware. Within the presented approach, context is used to *combine* the benefits of subsumption reasoning and similarity-based retrieval. It is defined as a set of concepts from the provider's application ontology that, after reclassification (comparable to the Lutz & Klien approach [4]), are subconcepts of C_{lcs}[4]: (Context = $\{C \mid C \sqsubseteq C_{lcs}\}$). In other words, context determines the universe of discourse (called application domain in [7]). In the presented accommodation scenario, C_{lcs} guarantees that all concepts proposed to be similar to Botel at least act as accommodations (subconcepts of Housing). Therefore similarity to cargo ships or ferries would not be measured, although they are kinds of boats as well.

After their expansion to WSML normal form, concepts are lists of attributes (with restrictions for their fillers), including also those inherited from their ancestors (via the *subconceptOf* constructor). For attributes with concepts as fillers, similarity is determined as specified in Equation 1[5] and depicted in Figure 3.

$$sim_{ac}(ac_s, ac_t) = \frac{\omega_a * sim_a + \omega_c * sim_o}{\omega_a + \omega_c} \begin{cases} sim_a \geq sim_o : \omega_a = 1 - |sim_a - sim_o|;\ \omega_c = 1 + |sim_a - sim_o| \\ sim_a < sim_o : \omega_a = 1 + |sim_a - sim_o|;\ \omega_c = 1 - |sim_a - sim_o| \\ (sim_a) \cup (sim_o) < t :\ \omega_a = 0;\ \omega_c = 0 \end{cases} \quad \textbf{(1)}$$

Sim_{ac} is the weighted average of the similarity (sim_a) derived by comparing the attributes a_s to a_t and the similarity obtained by measuring the overall similarity (sim_o) between the concepts (fillers) c_s and c_t; where *s* is the abbreviation for *search* and *t* for *target* (or *compared-to*). The attribute and concept weightings (ω_a and ω_c) reflect the relative importance of sim_a and sim_o within sim_{ac} and are defined in terms of the absolute difference between attribute and filler similarity. If the inter-attribute and inter-concept similarities are close together, both have a similar impact on sim_{ac}, otherwise the lower similarity value gets a higher weighting. Moreover an addition threshold (*t*) can be defined that needs to be exceeded - otherwise sim_{ac} is 0.

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[4] The abbreviation was chosen to refer to the idea of the least common subsumer.

[5] Similarity between binary relations is calculated accordingly: sim_a for the relation and sim_o for the filler.

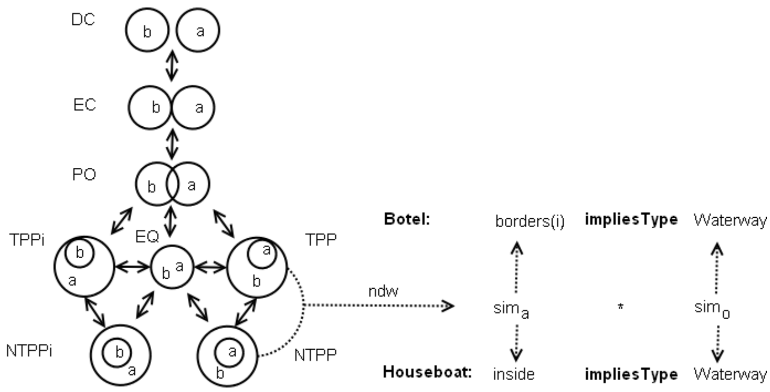

Figure 3. Spatial neighborhood distance [15] used to determine attribute similarity

Similarity between attributes (sim_a) can be determined in two ways: using a conceptual neighborhood distance (*ndw*), as depicted in Figure 3 for a topological neighborhood, or via the common subsumee similarity sim_{cs}. The benefit of conceptual neighborhoods is that they imply a very natural notion of similarity - which is just the inverse and normalized graph distance between the compared attributes (see Equation 2). Although the edge weightings may vary with respect to the chosen conceptual neighborhood (*n*), they are usually set to 1 per edge and symmetric (see also [17, 18] for similarity measures between spatial scenes).

$$ndw(a_s, a_t) = \frac{max\_distance_n - distance_n(a_s, a_t)}{max\_distance_n} \qquad \textbf{(2)}$$

In contrast, the common subsumee approach assumes that attributes are more similar if they share more common sub-attributes. In Equation 3[6] sim_{cs} is defined as the ratio between the number of subsumees of both attributes and the number of sub-attributes of one or both of them (where all y are elements of the context set). Note that within WSML-Core the sub-attribute relationship is specified as implication using logical expressions [14; p.29].

$$sim_{cs}(x_s, x_t) = \frac{|\{y \mid (y \sqsubset x_s) \sqcap (y \sqsubset x_t)\}|}{|\{y \mid (y \sqsubset x_s) \sqcup (y \sqsubset x_t)\}|} \qquad \textbf{(3)}$$

If compared attributes are neither arranged within a neighborhood and no global sub-attribute axioms are defined, similarity is determined by symbol matching. As each symbol (identifier) is unique within a WSML ontology, similarity is 1 if a_s and a_t share the same symbol for *a*, otherwise it is 0. This kind of matching can be refined using WordNet synsets for symbol comparison such as in MSDM [7].

As can be seen from Equation 1, the inter-attribute similarity sim_{ac} calls the overall similarity sim_o to determine the overlap between involved concept fillers. The overall

[6] The letters *x* and *y* indicate that the same equation is applied to attributes and base concepts (see below).

similarity (see below), however, again invokes sim_a to compare the attributes specified for these concepts and so on. The process terminates when the concepts specified as fillers have no concept description, i.e. are base symbols (primitives) of the shared vocabulary. Their similarity is determined according to Equation 3, where the subsumees are not attributes but subconcepts. The same approach is applied if super concepts defined in the head of concept definitions are base symbols and therefore do not bequeath attributes to their subconcepts (see Figure 2).

While the former paragraphs focused on concepts as attribute fillers, the similarity between attributes with datatype fillers is determined according to Equation 4. The function *match()* returns 1 if d_s and d_t are the same types or if all instances of d_s could be converted to d_t without losing information (respectively precision; such as from integers to decimals [14; p.88]); otherwise *match()* returns 0. Some problems related to similarity with respect to datatypes are discussed in the further work section below.

$$sim_{ad}(ad_s, ad_t) = sim_a(a_s, a_t) * match(d_s, d_t) \tag{4}$$

Finally, the overall similarity (Equation 5) between the search and compared-to concept is the normalized sum of the similarities derived by comparing attributes with concept fillers, attributes with datatype fillers and primitive concepts in the head of c_s and c_t. The normalization factor σ is just the count of the elements ($|S_{ac}|+ |S_{ad}|+ |S_c|$) selected for the directed comparison.

$$sim_o(c_s, c_t) = \frac{1}{\sigma}\Big(\sum_{(ac_s, ac_t)\in S_{ac}} sim_{ac}(ac_s, ac_t) + \sum_{(ad_s, ad_t)\in S_{ad}} sim_{ad}(at_s, ad_t) + \sum_{(c'_s, c'_t)\in S_c} sim_{cs}(c'_s, c'_t)\Big) \tag{5}$$

Referring to the accommodation scenario it turns out that *Botel* is more similar to *Hotel* (0.67) than to *Houseboat* (0.62) and *Youth_Hostel* (0.5). However, the measured similarities depend on the representation of the compared concepts within the provider's ontologies. Services focusing on vessels instead of accommodations may use different conceptualizations, making *Botel* and *Houseboat* more similar. Note that from now on the accommodation service can also display botels on the portal's website whenever a user is looking for hotels in Amsterdam, but (in contrast to subsumption-based retrieval) integrating the concept *Botel* into the local knowledge base would lead to inconsistencies (a botel is not a building).

3 Discussion and Further Work

The directed and context-aware similarity theory presented within this paper is able to measure the overlap between concept descriptions specified using WSML-Core, and can therefore support integration and retrieval within service oriented architectures. In contrast to previous work, it points out possible ways of combining subsumption reasoning and similarity. Nevertheless, a lot of work remains to be done to apply these initial results to sophisticated real world scenarios.

It turns out that while the comparison of attributes (respectively relations) restricted by concept fillers is well examined [9-11], the question how to develop a meaningful theory for datatype similarity still remains unsolved. One of the main reasons is missing information [19] about the level of measurement. For instance, the category of a hotel is measured in stars and represented as an integer on an ordinal scale; while the distance to a beach is also of the datatype integer but on an interval scale: 100 meters to the beach is half as much as 200 meters, but a 2 star hotel is not half as good as a 4 star hotel. In addition, according to Equation 4, the match function returns 0 for comparing decimals to integers, although the lost precision may not be relevant for a user in a certain situation. Taking complex XSD types into account would further complicate the determination of a meaningful notion of datatype similarity (e.g. xs:sequence).

Another important issue is the extension of the presented approach to cope with more expressive WSML variants. The major question arising here is what can be said (in terms of similarity) about compared logical expressions. While the presented theory demonstrates how to compare concepts within WSML service ontologies, mediators, goals and capabilities were not discussed within this paper. However further theories may benefit from the idea of WSML mediators as mapping rules [2]. Moreover it has to be examined how users, such as the service provider, can phrase search concepts without being domain experts and trained logicians.

References

1. OWL-S. *OWL-S 1.0 Release: www.daml.org/services/owl-s/1.0/.* (14/09/2006).
2. WSMO, *D3.1v0.1 WSMO Primer: www.wsmo.org/TR/d3/d3.1/v0.1/.* (14/09/2006).
3. WSMO, *D4.1v0.1 A Conceptual Comparison between WSMO and OWL-S: www.wsmo.org/TR/d4/d4.1/v0.1/.* (14/09/2006).
4. Lutz, M. and E. Klien, *Ontology-Based Retrieval of Geographic Information.* International Journal of Geographical Information Science.(2006) **20**(3): p. 233-260.
5. Goldstone, R. and J. Son, *Similarity*, in *Cambridge Handbook of Thinking and Reasoning*, K. Holyoak and R. Morrison, (Eds.) Cambridge University Press: Cambridge (2004).
6. Janowicz, K., *Extending Semantic Similarity Measurement by Thematic Roles*, in *First International Conference on GeoSpatial Semantics, GeoS 2005, Mexico City*. Springer Verlag: Berlin. (2005) p. 137-152.
7. Rodríguez, A.M. and M.J. Egenhofer, *Comparing Geospatial Entity Classes: An Asymmetric and Context-Dependent Similarity Measure.* International Journal of Geographical Information Science. (2004). **18**(3): p. 229-256.
8. Gärdenfors, P., *Conceptual Spaces - The Geometry of Thought*. Cambridge, MA: Bradford Books, MIT Press. (2000)
9. Schwering, A. *Hybrid Model for Semantic Similarity Measurement*. in *4th International Conference on Ontologies, DataBases, and Applications of Semantics (ODBASE05)*. Agia Napa, Cyprus. Springer Verlag (2005).
10. d'Amato, C., N. Fanizzi, and F. Esposito. *A Semantic Dissimilarity Measure for Concept Descriptions in Ontological Knowledge Bases* in *The Second International Workshop on Knowledge Discovery and Ontologies*. Porto, Portugal (2005).
11. Janowicz, K., *Sim-DL: Towards a Semantic Similarity Measurement Theory for the Description Logic ALCNR in Geographic Information Retrieval*. R. Meersman, Z.

Tari, P. Herrero et al. (Eds.): SeBGIS 2006, OTM Workshops 2006, LNCS 4278, (2006) pp. 1681 – 1692

12. Hau, J., W. Lee, and J. Darlington. *A Semantic Similarity Measure for Semantic Web Services* in *Web Service Semantics Workshop 05 at WWW2005*. Chiba, Japan (2006).
13. Fensel, D. and C. Bussler, *The Web Service Modeling Framework WSMF.* Electronic Commerce Research and Applications (2002). **1**(2).
14. WSML, *D16.1v0.21 The Web Service Modeling Language WSML: www.wsmo.org/TR/d16/d16.1/v0.21/.* (14/09/2006).
15. Cohn, A.G., et al., *Qualitative Spatial Representation and Reasoning with the Region Connection Calculus.*. GeoInformatica (1997). **1**(3): p. 275-316.
16. Kuhn, W. *Modeling the Semantics of Geographic Categories through Conceptual Integration*. in *Geographic Information Science-Second International Conference (GIScience 2002, Boulder, Colorado)*.Springer-Verlag, Lecture Notes in Computer Science 2478 (2002).
17. Bruns, T.H. and M.J. Egenhofer, *Similarity of Spatial Scenes*, in *Seventh International Symposium on Spatial Data Handling (SDH '96)*, M.-J. Kraak and M. Molenaar, Editors.Delft, Netherlands. (1996) p. 31-42.
18. Li, B. and F.T. Fonseca, *TDD - A Comprehensive Model for Qualitative Spatial Similarity Assessment.* Spatial Cognition and Computation, (2006) **6**(1): p. 31-62.
19. Schade, S. (2005): *Sensors on the Way to Semantic Interoperability*. Proceedings GI-Days 2005: Geo-Sensor Networks - From Science to Practical Applications. ifgi-Prints 23(2005).