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An Algorithm and Implementation for GeoOntologies Integration

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Abstract. *Sharing information through the web is a practice that many organizations and users do daily. This generates a need of methodologies and tools for semantic integrating the obtained information. With the GIS community the scenario is not different, but the needs are a little different because of the particularities of the geographic data. In this paper we present G-Match, an algorithm and implementation for integration of geographic ontologies. Our proposal combines some mathematical foundations and existing technologies in order to achieve expressive results.*

Resumo. *O compartilhamento de informações através da web é uma prática utilizada diariamente por pessoas e organizações. Esta prática gera uma necessidade por metodologias e ferramentas que façam a integração semântica das informações obtidas. Na comunidade de SIG o cenário não é diferente, com o agravante das particularidades inerentes aos dados geográficos. Neste artigo nós apresentamos o G-Match, um algoritmo e implementação para a integração de ontologias geográficas. Nossa proposta combina alguns aspectos matemáticos com tecnologias existentes com o objetivo de alcançar resultados expressivos.*

1. Introduction

The high cost of the data acquisition for populating Geographic Information Systems (GIS) was, in the past, one of the main obstacles for its popularization. The Internet created a huge network where users, institutions and organizations can easily share information. However, if on one hand, this interchange offers lots of benefits, on the other hand it generates the need to address the heterogeneities among the information obtained from distinct sources. It worth nothing obtaining a third part information if its meaning is not known or cannot be inferred automatically.

One way of making the information's meaning more explicit is the use of Ontologies [Spaccapietra et al. 2004], also in the geographic field. Some efforts on creating geographic ontologies are found in [Apinar et al. 2005, Chaves et al. 2005] as well as the ISO 19109 standard.

As the ontologies may be created by different communities and thus heterogeneities problems may arise when integrating the information from two or more ontologies. A number of works and tools address the problem of integration (also known as alignment) for conventional, non geogarphic ontologies [Castano et al. 2006, Doan et al. 2004, Giunchiglia et al. 2005, Noy 2004]. However, as they are not designed or developed for dealing with the particularities of the GIS data, specifically with the spatial relationships [Kuhn 2002, Schwering and Raubal 2005], many times they do not achieve as good results as the one obtained with conventional information.

In this paper we present the G-Match, an algorithm and an implementation of a geographic ontology matcher. Taking as input two different geographic ontologies, it measures the similarities of their concepts by considering their names, attributes, taxonomies and conventional as well as topological relationships. Except for the name comparison, G-Match considers both the commonalities and the differences for measuring the similarity between two concepts.

The remaining of the paper is organized as follows. Some related work regarding geographic information integration are briefly presented in Section 2. A motivating example presented in Section 3. Section 4 comprises the G-MATCH algorithm explanation in details while the results of the execution of our implementation are addressed in Section 5. Finally, conclusions and future directions are discussed in Section 6.

2. Related Work

2.1. Ontology mediated integration

Rodriguez, Egenhofer and Rugg [Rodríguez et al. 1999] proposed an approach for assessing similarities among geospatial feature class definitions. The similarity evaluation is basically done over the semantic interrelation among classes. In that sense, they consider not only the IS-A (taxonomic) relations and the part-Of relations but also distinguish features (parts, functions and attributes) [Rodríguez and Egenhofer 2003]. In addition to semantic relations and distinguish features two more linguistic concepts are taken into consideration for the definition of entity classes: words and meanings, synonymy and polysemy (homonymy). Later work on using ontologies and based on the properties and operations of the set theory they determined semantic similarity among entity classes from different ontologies [Rodríguez and Egenhofer 2003], but not considering the geospatial classes.

Fonseca et al. [Fonseca et al. 2002] proposed an ontology-driven GIS architecture to enable geographic information integration. In that proposal, the ontology acts as a model-independent system integrator [Fonseca et al. 2002]. The work of Fonseca et al. [Fonseca et al. 2003]focuses on the application level, in which they can work on the translation of a conceptual schema to application ontology. A framework for mapping between ontologies and conceptual schemas defines the mappings between a term in a spatial ontology and an entity in a conceptual schema for geographic information is defined, after the formalization of both conceptual schema and ontology's elements.

Hakimpour and Timpf [Hakimpour and Timpf 2001] proposed the use of ontology in the resolution of semantic heterogeneities especially those found in Geographic Information Systems. The goal was to establish equivalences between conceptual schemas or local ontologies. Basically the process is done in two phases [Hakimpour and Geppert 2002]: First, a reasoning system is used to merge formal ontologies. The result of merging is used by a schema integrator to build a global schema from local schemas. In the last phase, they find the possible meaningful mappings in the generated global schema and by that establish the mapping of data between the databases. Then the data (instances) from the local schemas are mapped. This process is composed by three parts: entity mapping, attribute mapping, data transformation [Hakimpour and Timpf 2001].

Sotnykova et al. [Sotnykova et al. 2005] state that the integration of spatial-temporal information (both schema and then data) is a three-step process comprising pre-integration (resolution of syntactic conflicts), Inter-Schema Correspondence Assertions (ICAs) (resolution of semantic conflicts) and integrated schema generation (resolution of structural conflicts). For semantic conflicts they propose an integration language, which allows formulating correspondences between different database schemas. Part of the work concerns on how to integrate the schemas. Not regarding to rules, formalization or measures of similarities, but in terms of how much information the integrated schema must have.

Stoimenov and Djordjevic-Kajan [Stoimenov and Djordjevic-Kajan 2005] propose the GeoNis framework to reach the semantic GIS data interoperability. It is based on mediators, wrappers and ontologies. The use of ontologies was proposed as a knowledge base to solve semantic conflicts as homonyms, synonyms and taxonomic heterogeneities.

Matching the geographical objects based on the matching of their child objects is the proposal of Cruz et al. [Cruz et al. 2004]. They have designed and implemented a tool for aligning ontologies, proposing a semi-automatic method for propagating such mappings along the ontologies, especially those ones for land use. In their approach, there must be a global ontology that is the reference for the alignment (not combining or merging) of the local ontologies. Alignment is the identification of semantically related entities in different ontologies. The alignment process is semi-automate, which means that the values associated with the vertices may be assigned in two ways: as functions of the children vertices or of the user input. The user initially identifies the hierarchy levels in the two ontologies that are aligned. Then the alignment component propagates to the parent nodes.

2.2. Semantic annotation based integration

The Knowledge and Information Management (KIM) platform provides an infrastructure and services for automatic semantic annotation, indexing and retrieval of unstructured and semi-structure content. The ontologies and knowledge bases are kept in repositories based on cutting edge Semantic Web technology and standards including RDF repositories, ontology middleware and reasoning [Manov et al.]. The main idea behind KIM is the semantic annotation, which means that the system looks at the description of an entity searching for key words and then associates it with a concept in the ontology (central knowledge base). The spatial features of a concept are described in a KIMO's sub ontology. The goal was to include the most important and frequently used types of Locations (which are specializations of Entity), including relations between them (such as hasCapital, subRegionOf), relations between Locations and other Entities and various attributes.

2.3. Spatial relationship based integration

Focusing on the semantic relationships other than the taxonomic ones is the proposal of [Jiang and Conrath 1997]. Especially, the so called functional relations of concepts are of

interest, and are available in the glosses (descriptions) of the concepts. Doing that, it is possible to find that two concepts are semantically related even though are hierarchically not. The measurement of the concepts similarity, following the authors' approach, is to use conceptual regions, which means representing the concepts as n dimensional regions in a vector space i.e. the region is continuous completely closed and the hull of the region is convex. The measurement of semantic similarity between conceptual regions is based on applying previously defined distance measures [Schwering and Raubal 2005].
Detecting similarities between geospatial data considering different geometries was proposed by Belussi et al. [Belussi et al. 2005]. In that work the authors make a deep comparison on topological relationships pointing equivalences depending on the geometry of the involved objects.

3. Motivating Example

Let's consider the scenario bellow, where the ontology from Figure 1 has to be integrated with ontology from Figure 2. This example is quite simple, but complete in terms of the geographic usually found in geographic ontologies and the ones we address in this paper. Furthermore, a problem more specific to geographic ontologies and which is

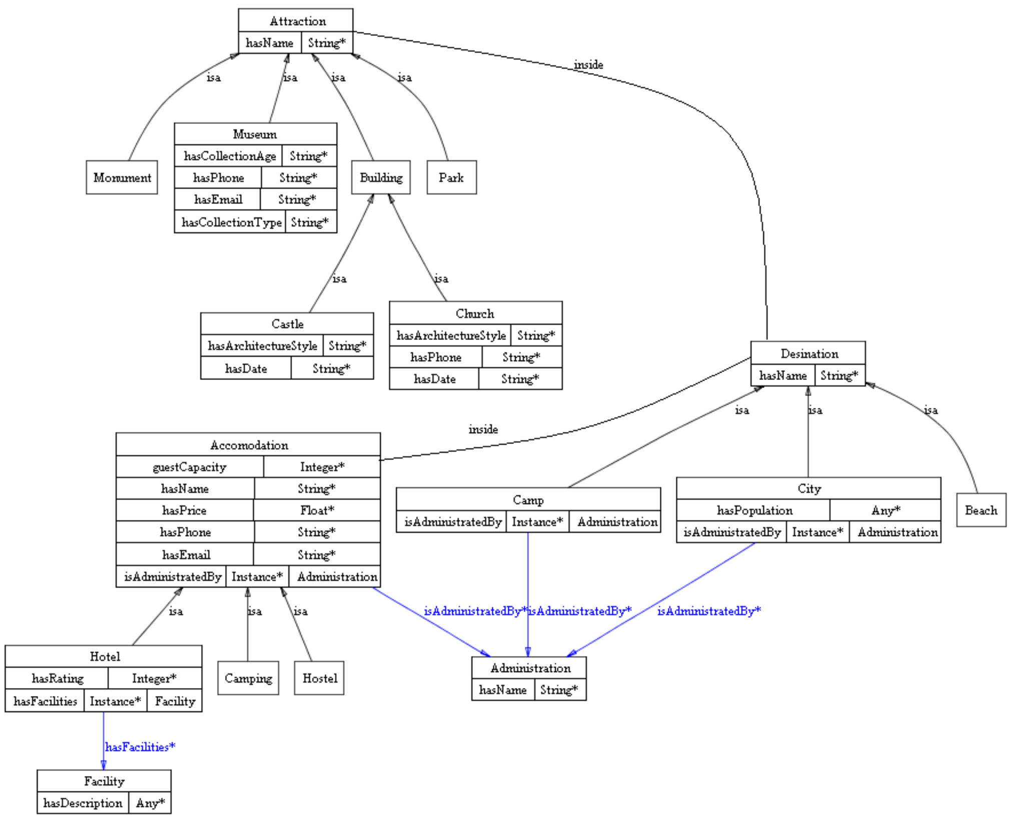

Figure 1. The ontology *O*

not supported by conventional matchers occurs when the concepts are designed using different ontologies. In these cases the different topological relationships may have the

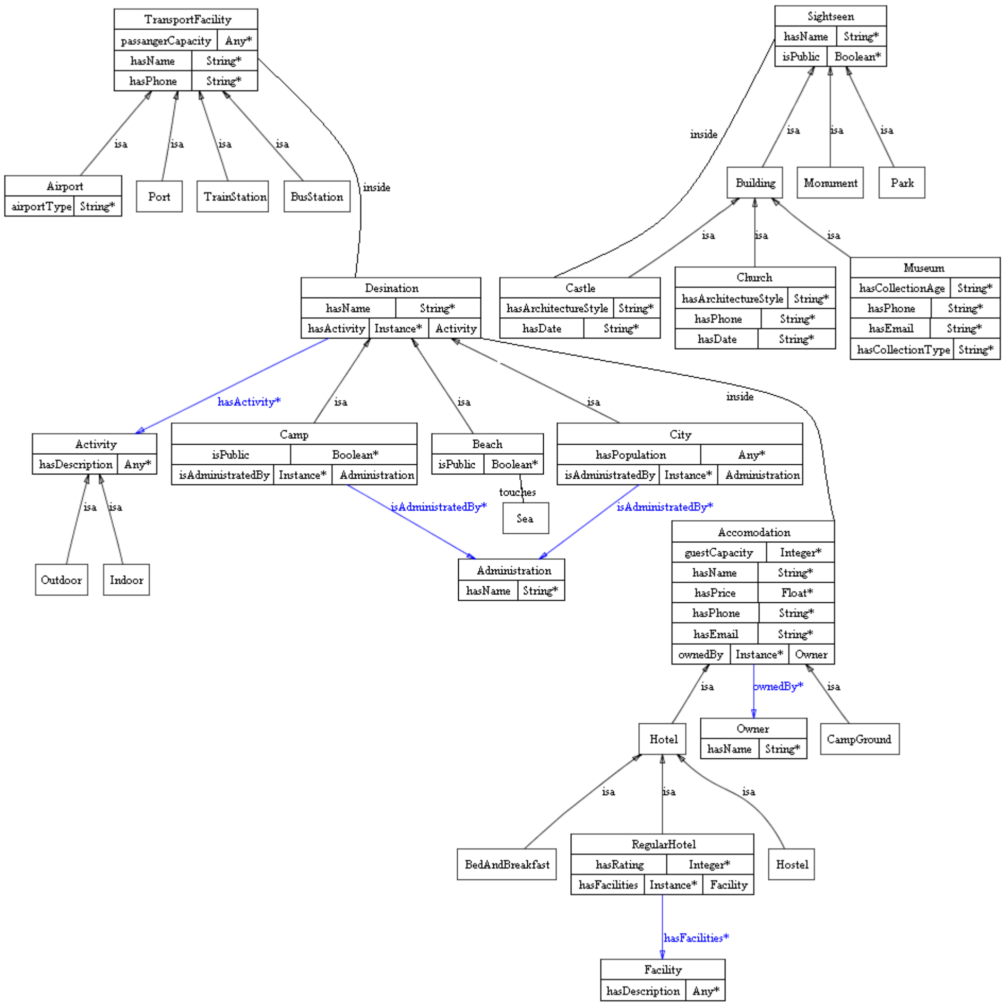

Figure 2. The ontology O'

same semantics, as stated in [Belussi et al. 2005] and illustred in Figure 3. Basically, the differences can be enumerated as follows:

4. G-Match

The G-Match algorithm is iterative, which means that each concept c_i from an ontology O is compared against all concepts $c_j$from ontology O'. Furthermore, the matching process is *n:n*, which means that more than one concept c_j from the ontology O' may be the match for a given concept c_i from ontology O. In this case, all the possible matches are presented to the user.

As Figure 4 shows, G-Match takes as input two ontologies O and O' and produces as output a list of similarity measures between the concepts from the two ontologies. The WordNet [Miller 1995] thesaurus is used by the name matcher and by the attributes matcher modules to find synonyms and related terms.

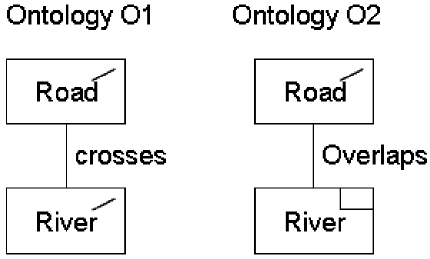

Figure 3. Equivalent topologies

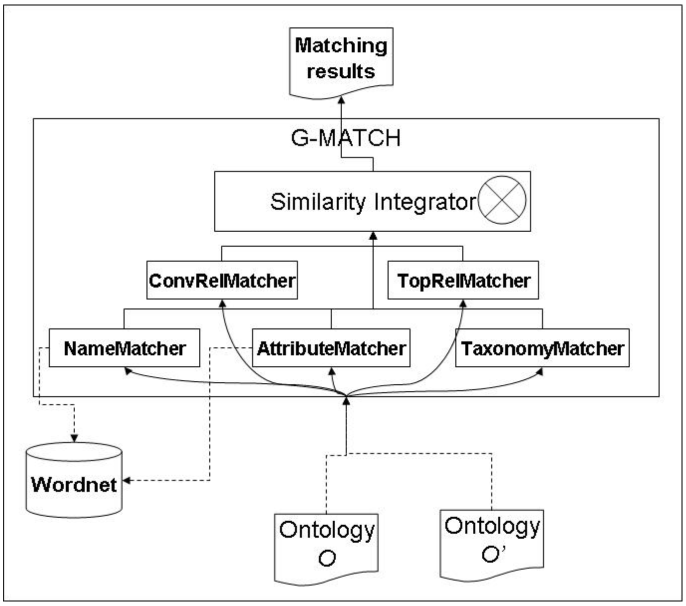

Figure 4. G-match architecture

4.1. Definitions

A geographic ontology may contain both geographic as non-geographic (conventional) concepts. Furthermore, it describes the properties of a concepts and the relationships it has with the other concepts.

Definition 1. *A concept c is a tuple of the form c = (T,S), where:*

- *T is the set of terms (synonyms) which nominates the concept c. A term* $t \in T$ *is defined as a unary relation of the form t(c);*
- *S = (h,P) is the structure of the concept c, where h is the hierarchy in which the concept c is located, defined as a unary relation h(c), and P = (A,R) is the set of properties of the concept c.*

  A is the set of attributes associated with c. An attribute $a \in A$ *is a binary relation of type a(c,dtp), where dtp is a data type (such as string, integer, etc.)*

  R is the set of relations of c with other concepts. A relation $r \in R$ *is a binary relation* $r(c,c')$*. Furthermore, a relation r =* $\{g,tr,cr\}$*, where g is a relationship between the concept c and a concept* c' *which denotes a geometry, tr is a topological relationship, i.e., a special type of spatial relationship between two geospatial* *concepts c and $c^{'}$ and cr is a conventional relationship between two concepts c and $c^{'}$.*

Definition 2. *A geospatial concept sc is defined as sc =* $\{c \in C \mid \exists\, r(c,c^{'}),\, r{=}g\}$ which means that a concept *c* is considered geospatial if and only if it has at least on relationship *r* of type *g*.

Definition 3. *At last, a relationship of type* tr *is defined as tr =* $\{r(c,c^{'}) \in R \mid (\forall\, c,c^{'},\, (c{=}sc \wedge c^{'}{=}sc)\}$ which means it can occur only between two geospatial concepts.

4.2. The Algorithm

The G-Match has three main phases of similarity measure in its execution, as the shown by the diagram of Figure 5. In the first one, the concepts names *(SimName(c_i),c_j)* and attributes *(SimAt(c_i),c_j)* are compared. Then, using the results from the name similarity measure, the taxonomies *(SimTx(c_i),c_j)*, relationships *(SimRel(c_i),c_j)* and topology relationships *(SimTop(c_i),c_j)* are evaluated. Finally, the last phase is the overall similarity measure. The algorithm's steps are detailed in the sequence.

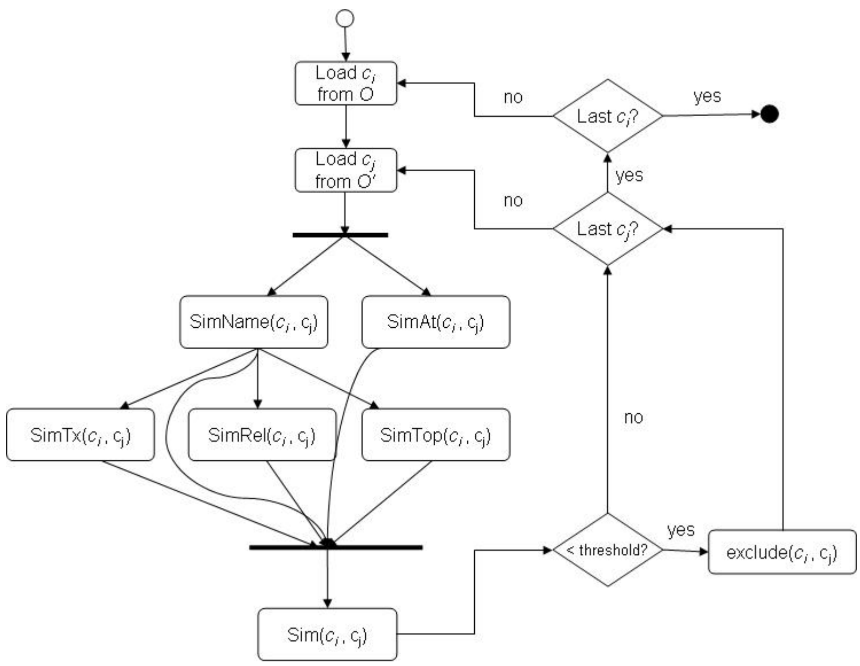

Figure 5. G-match execution flow

1. **Load concept c_i from ontology *O*.** A concept c_i is loaded.
2. **Load concept c_j from ontology $O^{'}$.** A concept c_j from the other is loaded to be compared against the concept c_i.
3. **Measure the similarity between the names of c_i and c_j.** Using the WordNet thesaurus as an auxiliary knowledge base, the name similarity *SimName(c_i,c_i)* is given by searching the correspondence of the two terms $t(c_i)$ and $t(c_j)$. In case the

WordNet returns 0 (not synonyms nor related) we calculate the string similarity of the terms using an adaptation of the metric proposed in [Stoilos et al. 2005].

4. **Measure the similarity between the attributes of c_i and c_j.** Once again we use the WordNet to assess the similarity between the terms used for each one of the attributes *a(*c_i*,dtp)* $\in$ *A(*c_i*)* against each one of the attributes *a(*c_j*,dtp)* $\in$ *A(*c_j*)*. In this case, however, we only consider to be a match if the terms are synonyms (or the same). The final similarity measure regarding the attributes is given by:

$$SimAt(c_i, c_j) = \frac{\sum((a(c_i) \cap a(c_j)) * Wa)}{A(c_i) \cup A(c_j)} \quad (1)$$

where *Wa* is the weight of the attribute *a* in the ontology. This weight is defined by the number of concepts *c* that are associated with this attribute. The more concepts, the more generic the attribute is and thus the lower is its weight.
The steps 3 and 4 can be executed in parallel.

5. **Measure the hierarchy similarity between c_i and c_j.** Based on the results obtained in the step 3, the similarity in terms of the concepts taxonomy is measured. This is done by checking the number of common sub-concepts the concepts c_i and c_j have and the level in hierarchy they are. The final value for the taxonomy similarity measure is given by:

$$SimTx(c_i, c_j) = \frac{\sum((h(c_i) \cap h(c_j)) * Wlevel)}{h(c_i) \cup h(c_j)} \quad (2)$$

where *Wlevel* is 1.0 if the subclasses are in the same level and 0.7 if they are in different levels in the ontologies.

6. **Measure the relationship similarity between c_i and c_j.** Again, using the results from step 3, the similarity of the conventional relationships is measured. This is done by simply counting the common relationships the two concepts c_i and $c_j$have in common and the different ones, as follows:

$$SimRel(c_i, c_j) = \frac{ass(c_i, r) \cap (c_j, r)}{(ass(c_i, r) \cup (c_j, r))} \quad (3)$$

7. **Measure the topological relationship similarity between c_i and c_j.** Again, using the results from step 3, the similarity of the topological relationships is measured. We considered here the ones described in [Egenhofer and Franzosa 1991] (disjoint, touch, inside, cover, coveredBy, overlap, equal, cross and contain). The similarity value is given by:

$$SimTop(c_i, c_j) = \frac{ass(c_i, t) \cap (c_j, t)}{(ass(c_i, t) \cup (c_j, t))} \quad (4)$$

For the topological relationships, it is important to clarify that we do not consider only the name of the relationship, but also the geometries of the concepts. As stated and deeply detailed in [Belussi et al. 2005] depending on the geometries of the concepts, the different topological relationship have the same meaning, that is, are equivalent. The G-Match is capable of detecting these equivalences during the similarity measurement, and this is the main feature that makes it more suitable for geographic ontologies than the conventional matcher.

8. **Measure the overall similarity between c_i and c_j.** In this step the similarity obtained in the previous steps are combined in a weighed sum, as follows:

$$Sim(ci, cj) = WN * SimName(c_i, c_j) + WA * SimAt(c_i, c_j) + \\ WH * SimTx(c_i, c_j) + WR * SimRel(c_i, c_j) + WT * SimTop(c_i, c_j). \quad (5)$$

9. **Non relevant matches discharge**. The pairs c_i,c_j with similarity values too low must be discharged, in order to produce less results and make it easy to choose the correct matches. Thus, a threshold parameter must be set in the beginning of the G-Match execution and if the similarity value for the pair c_i,c_j does not reach the threshold, it is discharged.
10. c_j **iteration**. If there are more concepts from ontology O' to be processed, return to step 2.
11. c_i **iteration**. If there are more concepts from ontology *O* to be processed, return to step 1.

5. Results

We executed the G-Match using as inputs the ontologies presented in the section 2. Basically, the differences can be enumerated as follows:

- The whole hierarchy of *TransportFacility* is present only in the ontology O';
- The concept *Attraction* from ontology *O* has as equivalent the concept *Sightseen* in ontology O';
- The most similar concept to *Hotel* from ontology *O* in ontology O' is *RegularHotel*;
- *Accommodation* in ontology *O* is associated with *Administration*, while in ontology O' the association is with *Owner*;
- In many concepts some attributes are present only in ontology O';

We implemented the G-Match in two ways: as a stand-alone, complete matcher (called G-Match complete) and as a extension for an existing matcher, as the ones cited previously, called G-Match. In the later case, only the relationships (conventional and topological) similarities were measured by our tool. The tests were run establishing as the minimum threshold for analysis 0.4.Table 1 shows the results in terms of recall and precision. EM denotes the expected matches, AM the automatic matches (i.e., similarity measured higher than 0.7) and CAM the correct automatic matches. As can be seen using a matcher specially tailored for the spatial relationships increases both the recall and precision. Furthermore, in the cases where the G-Match failed in choosing the correct match there were more than one pair (c_i, c_j) with similarity value higher than 0.7. The expected correct match was one of the returned pairs, but not the one with higher similarity. When the G-Match did not find any pair (c_i, c_j) with similarity higher than the acceptance threshold, the correct pair was within the ones with similarity higher than the analysis threshold.

6. Conclusion and Future Works

The challenge faced here was to develop a methodology that achieves good practical results when integrating two geographic ontologies by measuring their content similarities and differences. The similarity measure is balanced, that is, considers the features of

Table 1. Precision and Recall results

Matcher	EM	AM	CAM	Precision	Recall
Prompt	15	14	13	93%	87%
H-Match	15	12	10	83%	67%
G-Match	15	13	11	85%	73%
G-Match Complete	15	15	14	93%	93%

a concept separately and then gives some weights for each feature - name, attributes, taxonomy, conventional and topological relationships - to compute the overall similarity between two concepts. As the information may be defined in different levels of detail, there is not a perfect combination of the weight factors (WN, WA, WH, WR and WT). This combination depends on the characteristics of the input ontologies. The results obtained show that the G-Match is in the correct direction towards the development of a semantic matcher specially tailored for geographic ontologies.
As future work, we plan to study the impact of the other spatial relationships, such as distance relations, on the similarity measure between two ontologies. Furthermore, up to know the G-Match considers always all the features, independently of the concept being processed. Thus, if the ontology does not have, for example, topological relationships, the similarity measure decreases. Because of that, we intend to make the G-Match capable of self-adaptation depending on the input ontology, which means self-configuration of the weights WN, WA, WH, WR and WT.

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