Semantic Spatial Reasoning

Developing a Conceptual Framework for Reasoning with Semantic, Qualitative-Quantitative Spatial Information

Roman Katerinenko
Oracle Labs, Schiffbauergasse 14, Potsdam, Germany

Keywords: Qualitative Spatial Reasoning, Rule-based Reasoning, CDC, RCC-8, RDF, Semantic Web, OWL.

Abstract: In recent years, significant achievements have been made on handling qualitative spatial relations in the field of qualitative spatial reasoning. These achievements can be utilized to bridge the gap between geometries and semantics of real-world objects. With this purpose we introduce the Semantic Spatial Reasoning conceptual framework for reasoning with information of mixed types: qualitative-quantitative spatial and information described with the help of the Semantic Web technologies. The objective of this framework is not to be a particular reasoning algorithm but a conceptual decomposition suitable for showing benefits of the combined reasoning approach, forecasting practical applications and giving a clue for an implementation. Modular structure of the framework makes it useful to model various tasks in areas, such as, GIS, cognitive vision, computer-aided design, data integration.

1 INTRODUCTION

In recent years, significant achievements have been made on handling qualitative spatial (QS) relations in the field of qualitative spatial reasoning (QSR). QS relations are symbol abstractions of geometric representations which allow to use qualitative terms to formulate rules in order to describe spatial situations and actions. Normally, systems dealing with spatial information also capture it's semantics. Therefore, we decided to extend QSR with ability to reason with semantic information and introduced *Semantic Spatial Reasoning* (SSR) conceptual framework. In our investigation, we concluded that the abilities of our approach broader than often-considered constraint-based reasoning abilities of QSR because it allows to generate new spatially-enabled knowledge from existing knowledge.

Research in the field of QSR have been conducted in different directions, such as, design of and reasoning with QS calculi, their combination (De Felice, 2013) and effective implementation (Schneider, 2002). A wide variety of QS calculi has been developed to model different aspects of the space like topology (Region Connection Calculus, RCC-8), cardinal directions (Cardinal Directions Calculi, CDC), relative orientation, distance, visibility, shape, size. Herewith, there was a relatively small investigation of using the Semantic Web technologies in combination with QSR, mostly related to the improvement of quantification with the help of rules (De Felice, 2013).

From the opposite side, there are some efforts to develop spatial extensions of some Semantic Web technologies like GeoRDF and GeoSPARQL (Perry and Herring, 2012) but, regarding incorporation of QSR into this standards, only topology calculus (RCC-8) were added. Therefore, our goal is to bridge this gap by the development of SSR.

In this article we introduce a conceptual framework for SSR which allows reasoning with different types of information — semantic, qualitative-quantitative spatial. The objective of this framework is not to be a particular reasoning algorithm but a conceptual decomposition suitable for showing benefits of the combined reasoning approach, forecasting practical applications and giving a clue for an implementation.

2 BASIC ELEMENTS

Coad and Yourdon (Coad and Yourdon, 1991) concluded that it is natural for human to use the object-oriented approach for thinking about real world: differentiation of experience into particular objects, dis-

Katerinenko, R..
Semantic Spatial Reasoning - Developing a Conceptual Framework for Reasoning with Semantic, Qualitative-Quantitative Spatial Information.
In *Proceedings of the 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2015) - Volume 2: KEOD*, pages 257-262
ISBN: 978-989-758-158-8

tinction between the whole object and it's part and distinction between different classes of objects. The Semantic Web technologies like RDF and OWL have successfully utilized this approach and added a very important concept of a *relation* which is used to reflect arbitrary dependencies between real-world objects. When considering objects having spatial extent (spatial objects) qualitative spatial (QS) relations are normally used to handle information which can include concepts, such as, "inside", "next-to", "part-of" rather than geometrically specific data with numerical coordinates. These relations are studied in the field of Artificial Intelligence called *Qualitative Spatial Reasoning* (QSR). So we can conclude that QSR and the Semantic Web technologies have a common ground — object-oriented approach, thus it is a natural thing to investigate possibilities of the combined approach which we call *Semantic Spatial Reasoning* (SSR).

With a view to be semantically close to the object–oriented approach, we have included the following basic concepts to our model: *objects*, *classes*, *properties* of objects and *relations* between them. We distinguish two types of objects: the objects with known spatial extent (SE) and others. In the remainder of this article we refer to the former objects as O^s and to the latter as O. In the same way we distinguish two types of relations: QS relations and others which we call *semantic relations* for simplicity. QS relation (R^s) could be an arbitrary relation of any QS calculi, such as, CDC, RCC-8 or OPRA. Semantic relations (R^{sem}) express some other relations between objects, such as, administrative ("report-to"), family ("parent-of"), friendship ("who-likes-whom"), etc. Such distinction to spatial and not spatial elements allows us to analyze possible translation (mapping) functions between O^s, O, R^s, R^{sem} in the next section.

3 TRANSLATION OPERATIONS

In this section we introduce the next part of our conceptual framework — *translation operations* which perform translation or mapping between different types of the basic elements. We have analyzed all possible translation operations between objects, objects with SE, QS relations, semantic relations and have selected six meaningful. The *quantification* (see Section 3.2) and *qualification* (see Section 3.3) operations have been studied in literature but the others are our own contribution.

3.1 Translation Operations *Sem*, *Geom*

The *Sem* translation operation is supposed to define semantics for an object, so that this semantics could be used in the rule-based reasoning described in Section 4.2. In the Semantic Web technologies semantics of a real-world object is captured within it's relations to another objects. For example, given object's identifier as an input, the *Sem* operation could yield the semantic network containing information about object's class, properties and relations. Sometimes such semantic information is contained in geographic maps as a"thematic layer" or, in case of OpenStreetMaps, is contained in "tags" attached to objects.

The *Geom* translation operation yields object's SE which is used in the QS reasoning and the translation operations. The result could be a vector geometry stored in a spatial database or a text description kept in GeoRDF and turned to a vector geometry.

3.2 Quantification

The *quantification operation* was defined in (Wolter and Wallgrün, 2012) as the process of computing a geometric interpretation of a qualitative relation considering geometries of the reference objects. The computation is based on the geometric semantics of the relation. For most qualitative calculi quantification hasn't been studied yet, but for CDC and RCC-8 it can be implemented relatively simple.

We have extended this notion to use with objects and several calculi simultaneously: the *quantification operation* approximates a possible SE of O^* (with asterisk we mark objects with unknown SE) by quantifying all QS relations $R^s(O^*, O_1^s, \ldots, O_n^s)$ associated with it. More precisely the quantification of O^* is computation of a spatial region that the real-world entity represented by O^* can occupy in order to satisfy all QS relations $R^s(O^*, O_1^s, \ldots, O_n^s)$ with respect to the reference objects $O_1^s, \ldots, O_n^s$. The quantification is impossible when SE for all reference objects are unknown. As a result O^* gets not just an exemplar region which satisfies the relations but the maximum region which is union of all possible exemplar regions.

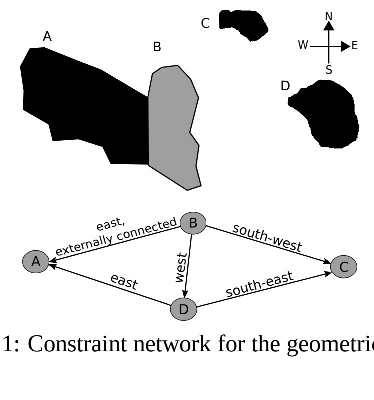

Figure 1: Constraint network for the geometric scene.

For example, if it was required to quantify object B shown in Figure 1 then the quantification operation could compute the region shown in Figure 2. Obviously, the quantified region is less precise than the real-world object, but the more objects and relations are involved the more precise the result is. In our notation the quantification operation expressed as follows:

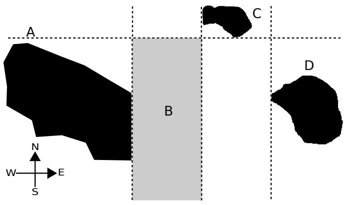

Figure 2: Quantification of object B.

$$Quantification : O^*, R^s(O^*, O^s_1, \ldots, O^s_n) \mapsto O^s$$

3.3 Qualification

The opposite to the quantification operation is the *qualification operation*. It yields the QS relation which holds between objects with SE:

$$Qualification : O^s_1, \ldots, O^s_n \mapsto R^s(O^s_1, \ldots, O^s_n)$$

Given that the system contains several calculi, the quantification operation requires to check the constraints which every calculus defines for the objects in a all relations. For example, to qualify a relation in the system containing RCC-8 and CDC calculi the quantification requires to check whether the objects overlap, disjoint, one object is located to the north of another, etc.

3.4 Translation Operations TO_1, TO_2

Previously, we have considered four elements of our framework: objects in general, objects with known SE, QS relations and translation operations between them (quantification, qualification). Now we are adding the rest part of our model — semantic objects, rules, relations and considering possible translation operations between whole elements of the model.

At first, we consider the mapping between an arbitrary semantic relation and a QS relation for the same objects: $R^s(O_1, \ldots, O_n) \leftrightarrow R^{sem}(O_1, \ldots, O_n)$. The Semantic Web technologies allows to define any arbitrary relation but we do think the restriction for this translation operation is those semantic relations which have synonymic QS relations. For example, one could define an RDF relations, such as, "next-to","close-to", "near" which, could be mapped to the "externally connected" RCC-8 relation. So CDC relations, such as,"north", "east" could be mapped to the "in-front-of" and "to-the-right" RDF relations. In other words, this translation operation allows to utilize QS relations during the rule-based reasoning and utilize semantic relations during the QS reasoning.

For more thorough analysis we divide this translation operation into two separate operations (TO):

$$TO_1 : R^s(O_1, \ldots, O_n) \mapsto R^{sem}(O_1, \ldots, O_n)$$

$$TO_2 : R^{sem}(O_1, \ldots, O_n) \mapsto R^s(O_1, \ldots, O_n)$$

In general, TO_1 should be treated not just as a mapping but as the operation which defines semantics of an object taking into account it's QS relations with another objects. An exemplar implementation could accept inputs as: a geometric scene; QS relations between the objects of the scene; geographic or administrative semantics for some of them, such as, "building", "bridge", "river"; etc. Afterwards, TO_1 yields a semantic description of the scene, such as, "An unknown object O^* is connected to particular road and overlaps particular river" but in the form of a semantic network. This semantic network could be turned into a SPARQL query to search the RDF concept for O^* in some RDF graph. This RDF concept could be treated as semantics of O^*.

We admit that some geographic feature recognition or image analysis algorithms could do this job as well and decide that O^* is likely a "bridge", but our approach could find the name of the bridge if the RDF graph is detailed enough. Also probabilistic machine learning models could be utilized for TO_1 implementation.

Considering TO_2, there are two cases. In case when all SEs of $O_1, \ldots, O_n$ are known, TO_2 is just a mapping between synonymic relations . In case, there is an object O^* with unknown SE this operation (in combination with quantification) could determine it. As an exemplar scenario, let us consider the following news message: "Undefined object is between the church and the railroad and close to the bus stop". This information could be captured as an RDF graph. Moreover, SE of the church, the railroad and the bus stop are known from the map of the city. So afterwards, TO_2 yields constraint network (similar to the one shown in Figure 1) consisting of QS relations and one object with unknown SE, which could be computed later by the quantification operation.

Mentioned scenario is related to the task of computation of quantitative spatial scene by it's text, video or speech description. In general, the result geometry is not a perfect match with the real-world geometry of the object but this approximations is especially useful in case of observations when precise coordinates of the observable object are not available or not needed, such as, "crowd movement" observation.

Comparing to a conventional quantification, the combination of *Sem*, TO_2 and quantification can achieve a better result and compute SE more precisely because it is possible to utilize semantic information about object's geometry, such as, shape or size. In our framework this information could be kept in the *class* of an object. For example, the information that the target object is instance of a car-like shape class could be accounted during the quantification process. We think that investigation of this possibility is related to the idea of using real algebraic geometry for the quantification suggested here (Wolter and Wallgrün, 2012).

3.5 Translation Operations TO_3, TO_4

These two translation operations are different from the others because their purpose is to produce new objects. Introduction of new objects during reasoning process is not a typical situation for a reasoner. For instance, Semantic Web reasoners are supposed to introduce new relations between entities, but not new entities. Datalog-style reasoners are the same. But, sometimes, such feature is needed for the application purposes. So that Oracle Database supports this feature in combination with user-defined rule reasoning.

In our notation TO_3, TO_4 are expressed as follows:

$$TO_3 : R^{sem}(O_1^s, \ldots, O_n^s) \mapsto O^s$$

$$TO_4 : R^s(O_1^s, \ldots, O_n^s) \mapsto O^s$$

The idea of both operations is the same, but TO_3 is designed to compose a new object by semantic relations while TO_4 accepts QS relations. New object is the result of application of geometric operations to $O_1^s, \ldots, O_n^s$ input objects with known SE. The geometric operations could be of any kind, such as, computation of union, difference, convex hull, etc.

For example, in a particular application TO_4 could be implemented in the following way: if O_1^s is a "house", O_2^s is a "garden" and R^s is "externally-connected" RCC-8 relation between O_1^s and O_2^s then TO_4 yields new object O^s "household" which SE is geometric union of O_1^s and O_2^s regions.

4 SEMANTIC SPATIAL REASONER

In this section we introduce architecture of the *semantic spatial reasoner*. We have developed it with the aim to show great possibilities of combined reasoning process utilizing the translation operations described in Section 3.The reasoner (see Figure 3) consists of two major modules: QSR and rule-based reasoner. They run in a loop until fixpoint state is reached and no new information can be inferred anymore.

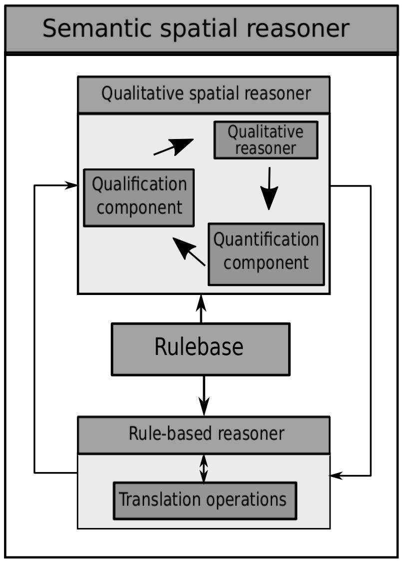

Figure 3: Semantic spatial reasoner architecture.

4.1 Qualitative Spatial Reasoner

This module was introduced in (De Felice, 2013) as a system for integration of quantitative and QS information. For this purpose it contains three components: *qualification*, *quantification* components and *qualitative reasoner*. We have added QS reasoner to our framework in it's original meaning but with one extension — we added ability to influence the quantification component by semantic rules. The reason for that will be discussed in Section 4.3.

All three components operate on the same data structure — the constraint network in which the edges are labeled with relations from QS calculi; the nodes correspond to the objects with known or unknown SE. The quantification component applies the quantification operations (see Section 3.2) to every object with unknown SE in order to find it's possible geometry with respect to the constraints (relations). Afterwards, the qualification component applies qualification operation (see Section 3.3) to every object in order to deduce it's QS relations with the others. The next turn is for qualitative reasoner which is based on *algebraic closure* or *path consistency algorithm* (Mackworth, 1977) that applies composition and permutation operations defined in a calculus to propagate the constraints through the network and infer as much new relations as possible. Main loop continues while information in the constraint network is changing. When fixpoint is reached the *rule-based reasoner* steps into the reasoning process.

4.2 Rule based Reasoner

By the *rule-based reasoner* we mean a reasoner which applies rules to some information and deduces new information complied with the rules. This type of reasoning is known as a *forward chaining inference* or *bottom-up inference*. Such reasoning process finishes at a fixpoint state. A rule is an IF — THEN construction. If some condition (the IF part) that is checkable in some dataset holds, then the conclusion (the THEN part) is processed.

There are many types of rules with different syntax and semantics. In our framework we are using the Datalog-style rules (Katerinenko and Bessmertnyi, 2011). Such rules contain relations in both parts. For example, the fact that a car is parked in a parking might be expressed with relation like $parkedIn(car, parking)$. Adding the notion of variables, a rule could be something like:

$$IF\, parkedIn(?x, ?y)\, THEN\, ntpp(?x, ?y)$$

where "ntpp" stands for "non-tangential-proper-part" RCC-8 relation. It is expected that for every pair of $?x$ and $?y$ for which *parkedIn* relation holds, the rule-based reasoner can conclude that the $ntpp$ relation holds as well and the corresponding relation $ntpp(car, parking)$ is added to the dataset.

4.3 Rules as Constraints

Qualitative representations enable capturing conceptual knowledge while abstracting of complexity of real-world numeric information. Thus, it is a natural choice to use QS reasoning in conjunction with rule-based reasoning. But there is another possibility for cooperation — rules can be used as constraints to guide quantification. For example, it is possible to compose a rule from the statement "A river can not intersect a house" and use this rule during computation of SE for the house. This idea was presented in (De Felice, 2013) as additional to QS reasoner "thematic reduction" component, but in our case it is an integral part of the framework. Thus, the same rulebase could be used for this purpose and for rule-based reasoning.

5 COMBINED REASONING WITH THE TRANSLATION OPERATIONS

In this section we demonstrate how the translation operations enable mutually compliment reasoning. Let us consider an exemplar dataset of mixed information in order to demonstrate one iteration of the *semantic spatial reasoner*. For the simplicity we are considering dataset which has been converted to the form of a constraint network briefly discussed in Section 4.1. This network is shown in Figure 4, in which black circle nodes represent objects, square nodes represent objects with known SE, straight line edges represent QS relations and dashed edges represent semantic relations. For simplicity, we have omitted directions on the edges and considering only binary relations. Also let's assume that this network is the result of the first application of the QS reasoner to the dataset. For details of this process refer to (De Felice, 2013).

As it is expected, after QS reasoning all objects which have at least one relation with the object with known SE were quantified. Otherwise, the quantification operation are not able to compute geometry for it, like in case with triangular subnetwork in the left part (see Figure 4). The same way, all QS relations between objects with known SE were found. Application of the TO_1, TO_2 translation operations have added two new edges E_2, E_3 to the network (see Figure 5). The E_1 edge represents a QS relation appeared after application of TO_2 to the semantic relation of the E_1 edge. Now E_2 is adjacent to the object with known SE that means that SE for the second adjacent object will be found on the next invocation of the QS reasoner. In contrast to the E_2, edge E_3 appeared after application of TO_1 to the corresponding QS relation.

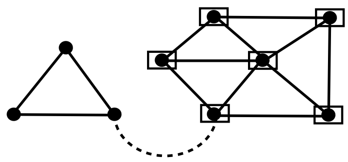

Figure 4: Exemplar constraint network.

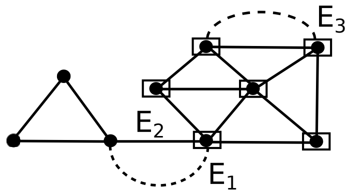

Figure 5: The network after TO_1, TO_2 application.

The next modifications are done by the *Sem* and *Geom* operations as shown in Figure 6. *Geom* has found SE for O_1 and *Sem* decided semantics for O_2. As it was mentioned in Section 3.1, in the Semantic Web technologies semantics of a real-world object is captured within it's relations to another objects, therefore new semantic edge was attached to O_2. This edge connects it to the semantic subnetwork, which could

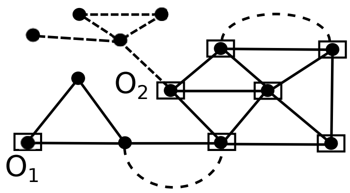

Figure 6: The network after *Sem*, *Geom* application.

be a subject for the QS reasoner on the next iterations, because O_2 has known SE.

On the next step new objects O_3, O_4 with known SE have been introduced by application of TO_3, TO_4 to the E_3, E_4 edges respectively (see Figure 7). Herewith, the E_3 edge has been introduced shortly before which demonstrates that the translation operations could be combined with each other in a meaningful ways.

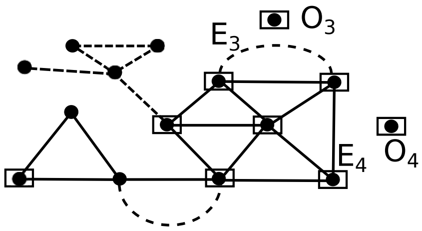

Figure 7: The network after TO_3, TO_4 application.

6 CONCLUSIONS

The aim of this work was to investigate reasoning with information of mixed types: qualitative-quantitative spatial and information described with the help of the Semantic Web technologies to bridge the gap between geometries and semantics of real-world objects. As a result we have introduced a conceptual framework called *semantic spatial reasoning*. We have developed the translation operations which are the main part of the framework that enables combined reasoning. Each operation opens a new direction for further research of it's software implementation and practical application in the context of the combined reasoning. We provided an exemplar idea for each operation.

The modular structure of the framework is flexible enough to model different practical tasks. For example, for the task of computing quantitative scene by it's text description one might need to implement the following elements of the framework: qualitative spatial reasoner, TO_4 and *Geom* translation operations. Such an easy decomposition makes the framework useful in different application areas, such as, GIS, cognitive vision, computer-aided design, data integration. Since declarative rules are the first class citizens of the framework, it makes possible to generate new spatially-enabled knowledge from existing knowledge, such as, generating implicit consequences of some spatial events like earthquakes, industrial disasters.

We plan to incorporate all elements of the framework into software application using existed reasoners and investigate reasoning capabilities of the result on real-world tasks in GIS area. We will also investigate how the framework could be generalized to adopt qualitative temporal reasoning.

ACKNOWLEDGEMENTS

This work was carried out in the framework of the ALErT project, European Union grant no. 607996.

REFERENCES

Coad, P. and Yourdon, E. (1991). *Object-Oriented Design*. Prentice-Hall.

De Felice, G. (2013). *Reasoning with mixed qualitative-quantitative representations of spatial knowledge*. Ios Pr Inc.

Katerinenko, R. and Bessmertnyi, I. (2011). A method for acceleration of logical inference in the production knowledge model. *Programming and Computer Software*, 37(4):197–199.

Mackworth, A. K. (1977). Consistency in networks of relations. *Artificial intelligence*, 8(1):99–118.

Perry, M. and Herring, J. (2012). Ogc geosparqla geographic query language for rdf data. version 1.0, ogc 11-052r4, open geospatial consortium.

Schneider, M. (2002). Implementing topological predicates for complex regions. In *Advances in Spatial Data Handling*, pages 313–328. Springer.

Wolter, D. and Wallgrün, J. (2012). Qualitative spatial reasoning for applications: New challenges and the sparq toolbox. *Qualitative Spatio-Temporal Representation and Reasoning: Trends and Future Directions*, pages 336–362.