Implementing Naïve Geography via Qualitative Spatial Relation Queries

Paolo Fogliaroni
Technische Universität Wien
Department for Geodesy and Geoinformation
Gusshausstrasse 27-29
1040 Vienna, Austria
paolo@geoinfo.tuwien.ac.at

Heidelinde Hobel
Technische Universität Wien
Department for Geodesy and Geoinformation
Gusshausstrasse 27-29
1040 Vienna, Austria
hobel@geoinfo.tuwien.ac.at

Abstract

Making Geographic Information Systems (GISs) "intelligent" is a fascinating idea that has challenged the GIScience community for decades and that, over the years, has been tackled from slightly different perspectives. In this paper we discuss the case of equipping GISs with the right tools to understand and address queries posed in a natural fashion from a human being. We discuss how this can be supported via a general type of spatial queries named Qualitative Spatial Relation Queries (QSRQ) that take on qualitative spatial relations formally defined in qualitative spatial calculi. After intuitively defining QSRQs, we categorize them and discuss the complexity of each category. Finally, we outline a processing framework to enable QSRQs in GISs.

Keywords: Naïve geography, Qualitative Spatial Representation and Reasoning, Spatial Databases, Qualitative Spatial Queries.

1 Introduction

Making Geographic Information Systems (GISs) "intelligent" is a fascinating idea that has challenged the GIScience community for a long time and that, over the years, has been tackled from slightly different perspectives.

It was exactly 20 years ago (in 1995) when Max Egenhofer and David Mark introduced the notion of Naïve Geography, [8] arguing that *"[...] GISs do not sufficiently support common-sense reasoning; however, in order to make them useful for a wider range of people [...], it will be necessary to incorporate people's concepts about space and time and to mimic human thinking"*.

A few years later (in 2007), Michael Goodchild coined the term Volunteered Geographic Information (VGI) [12] to denote the collective effort of gathering, within GISs, spatial information naturally acquired by human beings and of developing infrastructures to support this trend. Ever since, the rise of Web 2.0 allowed for a widespread diffusion of VGI projects such as Wikimapia[1], OpenStreetMap[2], and Google Earth[3] which, in turn, allowed for partially fulfilling the vision of Naïve Geography by bringing GIS to the reach of the general public.

However, GISs still lack, to a large extent, support for common-sense reasoning, as confirmed one year ago from Stephan Winter (one of AGILE 2014's keynote speakers) who challenged the GIScience community with his enlightening talk titled "Towards intelligent geospatial systems connecting location and place".

The contribution of this paper fits within this challenging scope of making GISs "intelligent" by providing them with common-sense reasoning capabilities. More specifically, we tackle the challenge of making GISs capable of automatically interpreting and resolving spatial queries expressed in natural language.

Drawing inspiration from the research field of Qualitative Spatial Reasoning (QSR) [3, 4]—a subfield of AI focused on the formalization of relational calculi capable of mimicking human spatial cognition—we introduce a family of generic spatial queries called Qualitative Spatial Relation Queries (QSRQ). We argue that, by encapsulating an arbitrary number of formally defined qualitative spatial predicates, these queries are valuable candidates to encode spatial descriptions expressed in natural language and, therefore, represent one possibility to bring GISs a step closer to understanding human beings. We also outline a processing pipeline to show how spatial descriptions expressed in natural language can be encoded into QSRQs and executed in a spatially-enabled database management system.

The remainder of the paper is structured as follows. Section 2 discusses previous relevant work. The QSRQ family is introduced in Section 3 along with a realistic running example, a list of different QSRQ's categories, and a discussion on their complexity. Later, in Section 4 we discuss the processing pipeline to go from natural language requests to query execution, we explain why QSRQs are not supported by present databases and discuss how this limitation can be overcome. Section 5 draws conclusions and discusses future research directions.

2 Related Work

The goal of providing GISs with common-sense reasoning capabilities has a long history. However, previous work along this direction has mainly been concerned with queries encoding topological relations [3]. Since their introduction in [7], topological relations have been continuously and deeply investigated and are the only qualitative relations that are currently implemented in most GISs. Other work [18] has also

[1] http://www.wikimapia.org

[2] http://www.openstreetmap.org

[3] https://earth.google.com

been devoted to the development of access methods to efficiently resolve topological queries.

In [9] a system to query spatial databases by sketch is described: the topological relations holding between the sketched objects are extracted and encapsulated in a SQL statement that is sent to the database.

The idea has been further refined in [19] to extract also other types of relations from a sketch but the focus has been mainly on deciding which types of relations are reliable, rather than on developing a general resolution technique.

To the best of our knowledge, the most similar approach to what is presented in this work is discussed in [23] and [20]. In [23] the authors suggest augmenting GIS capabilities by providing them with qualitative direction and distance operators, while in [20] a spatial SQL-encoding for a number of qualitative spatial relation is provided.

3 Qualitative Spatial Relation Queries

A Qualitative Spatial Relation Query (QSRQ) is a query that encapsulates a variable number of spatial predicates directly expressed as (or mappable onto) qualitative spatial relations formalized into one or more qualitative spatial calculi.

As a running example imagine the following scenario:

> Jane, an academic researcher, got a position at University of Bremen, Germany. As soon as she arrives in town, one of the first things she needs to do is to find an `apartment` to live in. Likely, she has some a-spatial constraints that the dwelling has to satisfy—e.g., number of rooms, rent price, and whether it is furnished or not. Moreover, Jane has the following spatial constraints: the `apartment` must be (*i*) *in between* the `university` and the `train station`, (*ii*) *close to* a `supermarket` and (*iii*) to a `tram/bus stop`. Finally, since Jane likes to relax by watching the horizon in the evening, she would like (*iv*) a green area, e.g., a `park`, to be *visible from* the `apartment`.

Figure 1: Part of the OSM dataset of the city of Bremen.

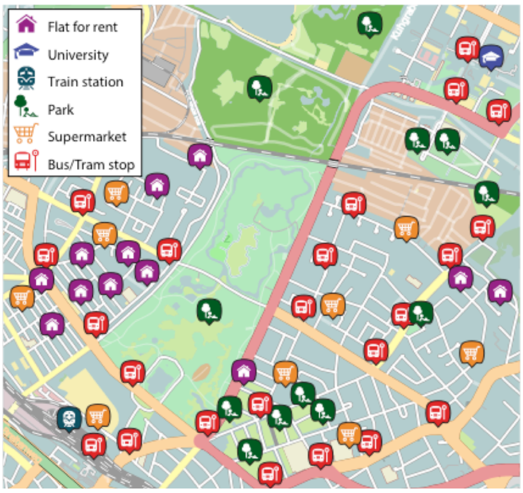


Figure 1 shows the part of the OpenStreetMap dataset of Bremen relevant for this example; icons denote entities of interest. The solution to spatial queries of this type consists of groups of entities *(i)* of a certain type and *(ii)* arranged according to a spatial configuration described in terms of qualitative spatial relations. In the given example, the entity types are `apartment`, `university`, `train station`, `supermarket`, and `tram/bus stop`; the qualitative spatial predicates are *in between*, *close to*, and *visible from*. Figure 2 shows the three configurations of entities that satisfy Jane's spatial query. Note that the bottom right apartment is part of two configurations (blue and magenta) as two different parks are visible from it.

Solving a QSRQ is equivalent to searching for all the entities in a given spatial dataset that are arranged as described in the query. In other words, the qualitative spatial relations expressed in the query have to be matched against those existing in the spatial dataset.

The matching problem is as much easier as the number of objects uniquely identified in the query increases: if one or more objects are specified by either their unique names, addresses, or geo-coordinates, the query difficulty scales down as the search can be "anchored" on such entities.

Accordingly, QSRQs can be classified by the *degree of indeterminacy* of the spatial predicates involved: For the sake of simplicity, assume the query consists only of one binary predicate of the form <object 1, spatial relation, object 2>. Also, assume that the spatial relation is taken from a set of B elements and that the spatial dataset on which the query is executed consists of N objects. Then QSRQs can be classified as depicted in Table 1.

Note that, given the typical cardinality of real geographic datasets, one can safely assume that $B<<N$. Therefore, the queries are sorted from top to bottom according to their complexity—i.e., the number of relations that have to be checked to resolve the query.

Naturally, a QSRQ can consist of several predicates of different levels of indeterminacy. In such cases, the product of the complexities of the individual predicates composing the query yields the overall complexity. Note also that spatial predicates can have an arity different than 2. In such case the exponent in the complexity column changes accordingly.

Figure 2: Solutions to the spatial query in the example.

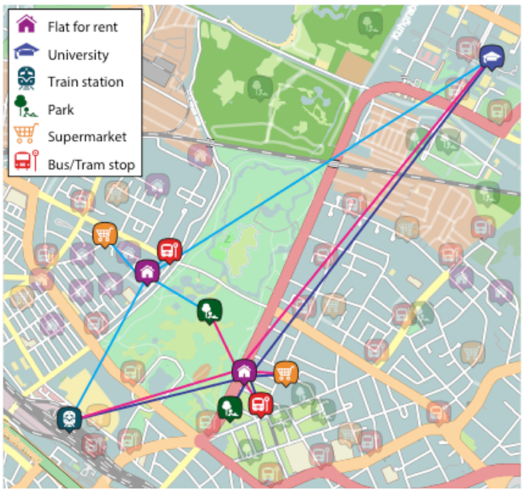


Table 1: Classification of Qualitative Spatial Relation Queries

Query Name	Spatial Predicate: Object 1	Spatial Predicate: Spatial Relation	Spatial Predicate: Object 2	Type of Spatial Request	Complexity
Relation Checking	given	given	given	Does the given relation hold over the given objects?	*O(1)*
Relation Retrieval	given	?	given	Which relation does hold over the given objects?	*O(B)*
Object Retrieval	? given	given given	given ?	Which objects are in the given relation with the given object?	*O(N)*
Object-Relation Retrieval	given ?	? ?	? given	Which relations do hold between the given object and the rest of the dataset?	*O(BN)*
Configuration Retrieval	?	given	?	Which objects are arranged according to the given relation?	$O(N^2)$
World Snapshot	?	?	?	How are the objects in the dataset arranged?	$O(BN^2)$

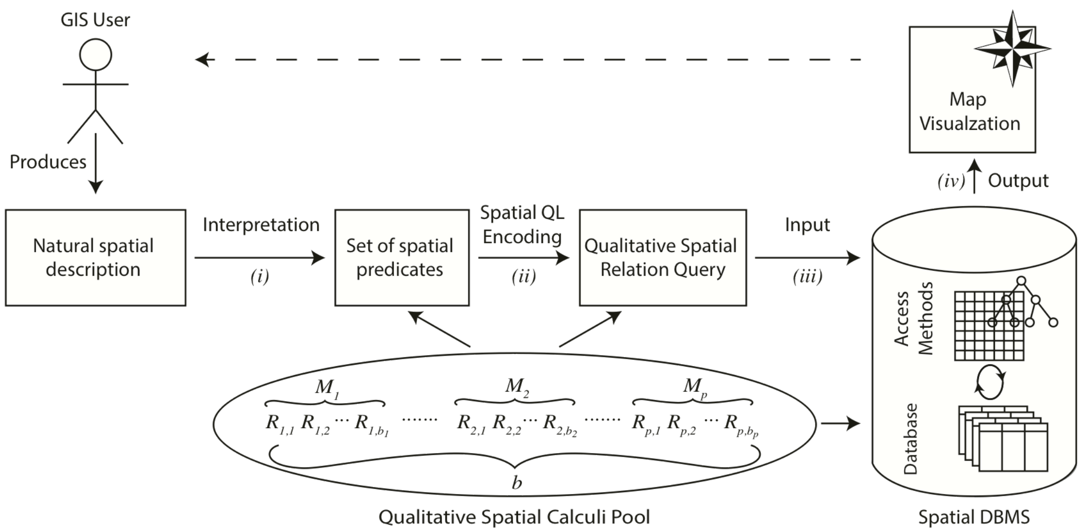
4 Processing Framework

Figure 3 depicts a processing framework for the automatic encoding and execution of QSRQs consisting of 4 phases that are discussed in the next subsections. The calculus pool represents the key element of the proposed approach: basically, it stands for an open number of qualitative spatial calculi, each providing a set of qualitative spatial relations that can be used in a query. Typically, each calculus focuses on one aspect of space, such as topology [7], relative [2] or cardinal [13] directions, distance [15], or visibility [11]. Since qualitative calculi provide formal definitions for the set of spatial relations they address, these can be straightforwardly implemented as spatial operators in the database underlying the GIS.

4.1 Interpreting Spatial Descriptions

The interpretation of spatial descriptions expressed in natural language is a challenging task that is actively investigated in the research community of Natural Language Processing (NLP). One main challenge is due to the ambiguity that spatial descriptions expressed in natural language typically carry along. Consider, for example, the utterance "the `supermarket` is to the *right*-hand side of the `cinema`". Does this mean that the supermarket is to the right-hand side of the speaker, as he stands in front of the cinema? Or is it to the right-hand side of the cinema, imagining the cinema to have a front (the façade with the entrance), a back, a right, and a left

Figure 3: Processing framework for QSRQs; from natural descriptions to query result



side? Typically, humans are capable of resolving such ambiguities from context [14]. They are also naturally talented at understanding from non-verbal signage when the interlocutor did not fully understand what has been communicated and at adjusting the levels of details accordingly [22]. The automatic interpretation of spatial descriptions expressed in natural language, therefore, should take these issues into consideration. Work on generating 3D scenes from textual descriptions is presented, for example, in [1, 4], while in [16] an approach to map spatial descriptions expressed in natural language onto projective spatial relations is discussed.

However, in the scope of this work we do not focus on these challenges. We assume that spatial descriptions expressed in natural language are interpreted and that the output of this process is (i) a set of variables constrained by (ii) a set of spatial predicates. For our running example we have a variable for each entity:

$$a \leftarrow \texttt{apartment},\ u \leftarrow \texttt{university},$$
$$s \leftarrow \texttt{train station},\ t \leftarrow \texttt{tram/bus stop},$$
$$m \leftarrow \texttt{supermarket},\ p \leftarrow \texttt{park}$$

and the following spatial predicates:

$$between(a, u, s),\ close(a, t),\ close(a, m),\ visible(p, a)$$

4.2 Spatial Query Language Encoding

As of today, GIS only provide topological and metric distance operators. This means that the set of predicates obtained in the previous step cannot be automatically encoded in a formal query language (say, for simplicity, spatial-SQL). Rather, a GIS expert has to take care of (*i*) interpreting the semantics of the predicates and (*ii*) encoding them into an SQL statement making use of the spatial operators available in the GIS.

Assume that Figure 4 represents part of the logical schema of the database that we want to query: the table Dwelling holds `houses` and `apartments`, the table Station maintains `train stations` and `tram/bus stops` and the table Amenities stores entities like `supermarkets`, `universities` and `parks`. Then, one possible SQL-encoding of the spatial predicates obtained above is depicted in Figure 5.

This is only one of the many possible interpretations of the qualitative spatial relation query in our example. This is precisely one point we want to emphasize here: since the qualitative relations are not defined in current GISs, the way they are encoded in a query relies heavily on how they are interpreted by the GIS user and on his knowledge about the spatial operators available in the GIS. In this particular

Figure 4: Part of the underlying database schema

Dwelling	
id:	*serial integer*
type:	*text*
name:	*text*
address:	*text*
for_rent:	*boolean*
the_geom:	*geometry*

Station	
id:	*serial integer*
type:	*text*
name:	*text*
the_geom:	*geometry*

Amenities	
id:	*serial integer*
type:	*text*
name:	*text*
address:	*text*
the_geom:	*geometry*

Figure 5: a possible SQL-encoding of the example QSCQ

```
1  SELECT
2     a.the_geom,  s.the_geom,  u.the_geom,
3     m.the_geom,  t.the_geom,  p.the_geom
4  FROM
5     Dwelling  AS  d,
6     Dwelling  AS  a,  Station   AS  m,  Amenities  AS  u,
7     Amenities  AS  m,  Station  AS  t,  Amenities  AS  p
8  WHERE
9     a.type  =  " Apartment "  AND  a.for_rent  =  true
10    AND  s.type  =     " Train Station "
11    AND  u.type  =     " University "
12    AND  m.type  =     " Supermarket "
13    AND  t.type  =     " Tram / Bus Stop "
14    AND  p.type  =     " Park "
15    AND  (distance (a.the_geom,s.the_geom)  +
16       distance (a.the_geom,u.the_geom))
17       <=
18       (distance (s.the_geom,u.the_geom)  +
19       (distance (s.the_geom,u.the_geom)/2))
20    AND  distance (a.the_geom,m.the_geom)  <  2
21    AND  distance (a.the_geom,t.the_geom)  <  2
22    AND  NOT  intersect (
23              set_difference (
24                 convex_hull (union (a.the_geom,p.the_geom)),
25                 union (a.the_geom,p.the_geom)
26              ),
27              d.the_geom
28          )
```

interpretation, for example, the following interpretations are done. First, the relation *between* has been considered satisfied by all those `apartments` (a) located within an ellipse, with eccentricity equal to 2 metric units, whose foci are the `train station` (s) and the `university` (u)—cf. lines 15-19. Second, the qualitative distance relation *close* has been interpreted as "less than 2 units away"—cf. lines 20 and 21. Lastly, the visibility constraint has been heavily approximated with the condition that no dwelling lies in between the searched `apartments` (a) and a `park` (p) —cf. lines 22-29.

The main reason hindering the automatic SQL-encoding is that the spatial predicates obtained in the previous step are not defined in present GISs. This is where qualitative spatial calculi come into play: a qualitative spatial calculus is a formal theory derived either from logical or geometrical properties that defines (*i*) a (usually) finite set of relations and (*ii*) inference rules. We are interested in calculi of the second category as they provide an explicit geometric interpretation of the semantics of the spatial relations.

We suggest integrating within GISs an open number of qualitative spatial calculi that we call a *calculus pool*. Each spatial relation provided by the calculi in the pool is implemented in the GIS as a Boolean function of the type $\mathtt{R}(\mathtt{o}_1,\mathtt{o}_2,\ldots,\mathtt{o}_n)$ that verifies if the relation `R` holds on the input geometries—where `n` is the arity of the relation. Under these conditions the SQL-encoding becomes a one-to-one mapping that can be done automatically. The result is depicted in Figure 6.

Figure 6: automatic SQL-encoding of the example QSCQ

```
SELECT
   a.the_geom, s.the_geom, u.the_geom,
   m.the_geom, t.the_geom, p.the_geom
FROM
   Dwelling AS a, Station AS s, Amenities AS u,
   Amenities AS m, Station AS t, Amenities AS p
WHERE
   a.type = " Apartment " AND a.for_rent = true
   AND s.type = " Train Station "
   AND u.type = " University "
   AND m.type = " Supermarket "
   AND t.type = " Tram / Bus Stop "
   AND p.type = " Park "
   AND Between(a,s,u)
   AND Close(a,t)
   AND Close(a,m)
   AND Visible(p,a)
```

The suggested processing framework should also be equipped with some mapping ontologies in the eventuality that the predicates extracted from the spatial description do not coincide with the relations in the pool.

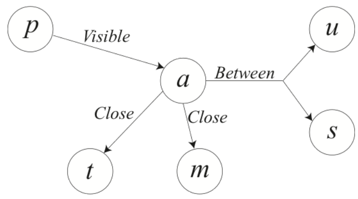
4.3 Qualitative Spatial Relation Query Execution

A QSRQ can be represented as a qualitative constraint network (QCN) [6] taking relations from multiple qualitative spatial calculi—i.e., a directed and edge-labelled hypergraph whose nodes represent the variables in the QSRQ and whose edges represent the qualitative relations among them. The QCN representation of the QSRQ corresponding to our running example is shown in Figure 7. Similarly, the spatial operators corresponding to the qualitative spatial relations provided by the calculus pool can be used to compute the qualitative relations holding among tuples of objects in the spatial dataset to be queried. The result of this operation is another QCN representing the whole spatial dataset.

Hence, solving a QSRQ is equivalent to identifying all the occurrences of the QCN representing the QSRQ within the QCN representing the dataset. This is a well-known problem in graph theory usually referred to as *subgraph isomorphism* or *subgraph matching*. Practically, a subgraph matching consists of assigning each node of the query graph one node of the dataset graph in such a way that (*i*) each node of the dataset graph is not assigned to multiple nodes of the query graph and (*ii*) the relations associated to tuples of nodes in the query graph match the relations associated to the corresponding tuples in the dataset graph.

If the query graph has n nodes and the data graph has N nodes, there are as many possible node assignments as the number of n-permutations of N elements without repetitions—i.e., $\frac{N!}{(N-n)!}$. All such assignments can be represented with a tree having as many levels as the number of nodes in the query graph. Each tree-node corresponds to a variable assignment. Tree-nodes at i-th level assign the i-th query graph node each data graph node that has not been assigned in upper levels. The root of the tree is located at level 0 and corresponds to the empty assignment. Accordingly, a path from the root to a leaf represents a complete assignment, but it is not guaranteed to be a matching.

Figure 7: QCN representation of the example QSRQ



To solve this problem, a modification of the well-known Ullmann's subgraph matching enumeration algorithm [21] can be employed: a breadth-first search on the assignment tree driven by the arc structure of the query graph with a forward checking on the arc labels. The search proceeds by e levels at once, where e is the number of nodes of the analyzed arc that have not been assigned yet. As the search proceeds, the forward checking rules out all the partial assignments that do not match with the query-subgraph induced by the arcs analyzed so far.

4.4 Result Visualization

The results of the subgraph matching are subsets of the objects in the queried spatial dataset arranged as in the given description. They can be returned, for example, as shown in Figure 2.

5 Conclusions and Future Work

In this paper, we tackled the challenge of making GISs capable of automatically interpreting and resolving spatial queries expressed in natural language. We disregarded the problems deriving from natural language interpretation and focused on the technics that GISs have to implement to accommodate for such requests.

To this end, we introduced the concept of Qualitative Spatial Relation Queries: a family of generic spatial queries that can accommodate for natural language requests. Unlike previous approaches, we drew a processing framework going from natural language interpretation down to query execution strategy at the database level. One main advantage relies on the generalization provided by our framework. Indeed, until today, spatial queries encoding different spatial relations have been studied independently and optimization techniques have also been developed independently. The introduction of a generalized query that can encapsulate any type of spatial relation and is resolved with a unique method (subgraph matching) will also allow for developing generalized optimization techniques [10]. Moreover, the presented framework allows for neatly splitting the tasks involved in the problem and for addressing them individually.

We did not discuss which qualitative relations are better suited to be implemented in GISs. This is work that has to be carried out in the future. Similarly, we completely disregarded the reasoning capabilities offered from spatial calculi. We believe that qualitative reasoning can also be exploited during query resolution (as done for example in [3]) to detect inconsistent requests but also to optimize qualitative representations and to boost the matching process.

References

[1] A.X. Chang, M. Savva, C.D. Manning, Learning Spatial Knowledge for Text to 3D Scene Generation, in: Proceedings of Conference on Empirical Methods in Natural Language Processing, 2014.

[2] E. Clementini, R. Billen, Modeling and computing ternary projective relations between regions, IEEE Transactions on Knowledge and Data Engineering. 18 (2006) 799–814.

[3] E. Clementini, J. Sharma, M.J. Egenhofer, Modelling topological spatial relations: Strategies for query processing, Computers & Graphics. 18 (1994) 815–822.

[4] A.G. Cohn, S.M. Hazarika, Qualitative Spatial Representation and Reasoning: An Overview, Fundamenta Informaticae. 46 (2001) 1–29.

[5] B. Coyne, R. Sproat, WordsEye: An Automatic Text-to-scene Conversion System, in: Proceedings of the 28th Annual Conference on Computer Graphics and Interactive Techniques, New York (NY), USA, 2001: pp. 487–496.

[6] R. Dechter, Constraint Processing, Morgan Kaufmann, 2003.

[7] M.J. Egenhofer, A formal definition of binary topological relationships, in: W. Litwin, H.-J. Schek (Eds.), Foundations of Data Organization and Algorithms, Springer Berlin Heidelberg, 1989: pp. 457–472.

[8] M.J. Egenhofer, D.M. Mark, Naïve Geography, in: A.U. Frank, W. Kuhn (Eds.), Spatial Information Theory A Theoretical Basis for GIS, Springer Berlin Heidelberg, 1995: pp. 1–15.

[9] M.J. Enenhofer, Spatial-Query-by-Sketch, in: Proceedings of IEEE Symposium on Visual Languages, 1996: pp. 60–67.

[10] P. Fogliaroni, Qualitative Spatial Configuration Queries: Towards Next Generation Access Methods for GIS, IOS Press,US, Amsterdam, 2013.

[11] P. Fogliaroni, J.O. Wallgrün, E. Clementini, F. Tarquini, D. Wolter, A Qualitative Approach to Localization and Navigation Based on Visibility Information, in: K.S. Hornsby, C. Claramunt, M. Denis, G. Ligozat (Eds.), Spatial Information Theory, Springer Berlin Heidelberg, 2009: pp. 312–329.

[12] M.F. Goodchild, Citizens as sensors: the world of volunteered geography, GeoJournal. 69 (2007) 211–221.

[13] R.K. Goyal, M.J. Egenhofer, Consistent queries over cardinal directions across different levels of detail, in: 11th International Workshop on Database and Expert Systems Applications, 2000. Proceedings, 2000: pp. 876–880.

[14] J. Hahn, A.U. Frank, Select the Appropriate Map Depending on Context in a Hilbert Space Model (SCOP), in: H. Atmanspacher, E. Haven, K. Kitto, D. Raine (Eds.), Quantum Interaction, Springer Berlin Heidelberg, 2014: pp. 122–133.

[15] D. Hernández, E. Clementini, P.D. Felice, Qualitative distances, in: A.U. Frank, W. Kuhn (Eds.), Spatial Information Theory A Theoretical Basis for GIS, Springer Berlin Heidelberg, 1995: pp. 45–57.

[16] J. Hois, O. Kutz, Natural Language Meets Spatial Calculi, in: C. Freksa, N.S. Newcombe, P. Gärdenfors, S. Wölfl (Eds.), Spatial Cognition VI. Learning, Reasoning, and Talking about Space, Springer Berlin Heidelberg, 2008: pp. 266–282.

[17] G. Ligozat, Qualitative spatial and temporal reasoning, John Wiley & Sons, 2013.

[18] D. Papadias, T. Sellis, Y. Theodoridis, M.J. Egenhofer, Topological Relations in the World of Minimum Bounding Rectangles: A Study with R-trees, in: Proceedings of the 1995 ACM SIGMOD International Conference on Management of Data, ACM, New York, NY, USA, 1995: pp. 92–103.

[19] A. Schwering, J. Wang, M. Chipofya, S. Jan, R. Li, K. Broelemann, SketchMapia: Qualitative Representations for the Alignment of Sketch and Metric Maps, Spatial Cognition & Computation. 14 (2014) 220–254.

[20] K. Stock, A geometric configuration ontology to support spatial querying, in: J. Huerta Guijarro, S. Schade, C. Granell Canut (Eds.), Connecting a Digital Europe through Location and Place. Proceedings of the AGILE'2014 International Conference on Geographic Information Science, Castellón, 2014.

[21] J.R. Ullmann, An Algorithm for Subgraph Isomorphism, Journal of the ACM. 23 (1976) 31–42.

[22] P. Weiser, A.U. Frank, Cognitive Transactions – A Communication Model, in: T. Tenbrink, J. Stell, A. Galton, Z. Wood (Eds.), Spatial Information Theory, Springer International Publishing, 2013: pp. 129–148.

[23] X. Yao, J.-C. Thill, Spatial queries with qualitative locations in spatial information systems, Computers, Environment and Urban Systems. 30 (2006) 485–502.