Inferring Complex Geographical Concepts with Implicit Geometries Using Ontologies: A Case of Peninsulas

Xiang Zhang, Tinghua Ai and Jantien Stoter

Abstract Ontology-driven concept inference has the merit of high flexibility and transparency. Users can composite and reuse atomic primitive concepts and relationship to interpret complex geographical concept without the need to retouch or even know the technical details. The major issue that we are focusing on is the implicit geometry problem. That is, the geometries corresponding to some primitive concept defining the complex geographic concept are missing or not fully represented in a spatial database, making it impossible to inferring the high-level semantics of the objects. This paper combines terminological/assertional inference (for general logic reasoning) and spatial operations (for making implicit geometries explicit), therefore enabling an ontology-driven inference of complex concepts that can handle cases where some concept has no explicit geometries. In the end, the concept of peninsula is used to demonstrate the proposed methodology.

Keywords Part-whole relations · Hierarchical structure · Terminological reasoning · Implicit semantics · Delaunay triangulation

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X. Zhang (✉) · T. Ai
School of Resource and Environmental Sciences, Wuhan University,
Wuhan, China
e-mail: xiang.zhang@whu.edu.cn

T. Ai
e-mail: tinghua_ai@163.net

X. Zhang · T. Ai
Key Laboratory of Geographic Information System, Ministry of Education,
Wuhan, China

X. Zhang · T. Ai
Key Laboratory of Digital Mapping and Land Information Application Engineering,
National Administration of Surveying, Mapping and Geo-Information, Wuhan, China

J. Stoter
Faculty of Architecture and the Built Environment, 3D GeoInformation,
TU Delft, Delft, Netherlands
e-mail: j.e.stoter@tudelft.nl

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1 Introduction

Inferring geographical concepts is concerned with finding the most specific semantics of the spatial objects. For instance, it is possible to infer house types (e.g. terraced house) or land-use types from bare geometry data (Lüscher et al. 2008). This is typically useful when users want to retrieve specific types of geographic features from a spatial database or via a spatial-enabled search engine.

However, information in current spatial databases typically covers basic topographic features and primitive semantics which are nonetheless not sufficient for the increasing need for complex spatial queries and semantic interoperation across information communities (Kuhn 2005; Klien 2007). Those queried spatial information usually includes complex geographic concepts (e.g. floodplain, terraced/semi-detached house) that commonly appear in natural languages, but that are not explicitly available in spatial databases. One challenge is thus concerning the semantic enhancement of geospatial data.

This paper takes one step further. We claim that, besides the lack of explicit semantics, the geometries required directly or indirectly for the spatial inference tasks are not always explicitly available in spatial databases, too. This brings about new challenges, e.g., triggering spatial algorithms during the logic inference to detect the implicit geometry. The implicit geometry issue in ontology-driven spatial data interpretation is a common issue in spatial information retrieval and semantic interoperation (Bennett et al. 2008), and may eventually decline the usefulness of the above-mentioned semantic enhancement practice.

This paper follows an ontology-driven approach to concept inference. We address the implicit geometry issue by combining the terminological inference with spatial operations. Specifically, certain algorithms are triggered on-demand to make implicit geometries explicit, before the reasoning proceeds with inferred semantics. Section 2 reviews related work. Section 3 is the core of the paper and describes the method in detail. Section 4 shows the feasibility of the method by applying it to the interpretation of peninsulas from spatial databases. The paper ends with discussion and conclusions (Sect. 5).

2 Related Work

2.1 Algorithmic Approach to Concept Inference

Many of the earlier spatial data interpretation techniques were motivated by the need of complex spatial information retrieval tasks. A basic assumption is that a lot of implicit information can be drawn from the geometric, topological and semantic relations encoded in spatial data (Sester 2000). Some of the techniques are based on graph theory, pattern recognition and statistical approaches, while some others adapt methods from spatial data mining (e.g. Regnauld 1996; Christophe and Ruas 2002; Steiniger et al. 2008).

However, these approaches consist of algorithms where the knowledge is hard-coded, and they can hardly be reused in a different context. Hence we consider them in the class of algorithmic approach. Furthermore, Lüscher et al. (2008) argued that it is doubtful whether the comprehensive interpretation of more general, higher-level geographic concepts can be accomplished by the purely algorithmic approach.

2.2 Ontology-Driven Spatial Data Interpretation

In automated map generalization, interpretation of hidden semantics is closely related to '*data enrichment*' (Neun et al. 2008). Traditionally, data enrichment techniques were developed and tightly coupled into sophisticated algorithms for specific tasks; see for example (Regnauld 1996; Christophe and Ruas 2002; Steiniger et al. 2008). This algorithm-driven approach was recognized by Sester (2000) and Lüscher et al. (2007) to have various weaknesses in applications where knowledge have to be made explicit.

In contrast, ontology-based approaches to the interpretation of geographic concepts have been increasingly adopted in recent years, where the interpretation is viewed as building a formal knowledge base for a domain on which reasoning processes are applied. The viewpoint is supported by recent developments in artificial intelligence (Baader et al. 2003; Möller and Neumann 2008). In the spatial domain, Lüscher et al. (2008) proposed an ontology-based model for urban pattern recognition. Later, they re-implemented the concepts using supervised Bayesian network (Lüscher et al. 2008), where the recognition process was manually translated from the ontology. This approach does not use the reasoning capability underlying ontologies. Similarly, Thomson and Béra (2007, 2008) showed the use of concept hierarchy to represent geographical concepts, and recommended *Description Logics* (DLs), a knowledge-formalism from artificial intelligence (Baader et al. 2003), but they did not implement the process. Nevertheless, we found that DLs is insufficient for the inference of geographical concepts because many concepts can only be recognized with algorithms that detect the spatial and/or part-whole relations between spatial objects. Hence to enable *spatio-terminological reasoning*, the inference process should be enriched with spatial computations.

In automated reasoning, the notion of spatio-terminological reasoning was proposed by Haarslev et al. (1994, 1998) aiming at integrating spatial calculation with logic-based reasoning process. The notion looks promising and we decide to follow this approach, but we will focus more in this paper on the issue of implicit geometries and how can it be integrated with the spatio-terminological inference.

3 Method

The idea of our proposed method is as follows. Our method firstly formalizes the primitive concepts and relationships by a set of generic spatial operations (including algorithms), and then formalizes complex concepts with an ontological language. This formalization declares the complex concept as a formal structure of primitive concepts. In the next step the complex concepts are automatically inferred using the spatially enriched reasoning techniques. This approach is highly flexible since the generic spatial operations can be reused when inferring different geographical concepts by only altering the knowledge defined in the formal language (knowledge driven rather than algorithm driven).

3.1 Generic Algorithms to Detect Primitive Relations and Implicit Geometries

Here we outline a triangulation-based data structure, on top of which proximity relations and implicit geometries (especially the part-whole geometries) can be obtained on the structure (Fig. 1). For example, it is easy to use this structure to model spatial proximity: any two objects that are connected by a triangle edge are immediate neighbors (e.g. *l* and *p* in Fig. 1b); narrow part (sub-region with implicit geometries) between two parallel roads *l* and *m* can be identified also on this structure (*c* in Fig. 1b). For a more detailed explanation to the structure and its operations, one may refer to Ai (2006).

Due to the relevance to the subject matter of this paper, we describe in more detail the shape descriptor and algorithm concerning a bend structure. The descriptors are derived with Delaunay triangulation based algorithms (Fig. 2a). The *bend segment* is the curve between $p1$ and $p2$; the link from $p1$ to $p2$ defines the *base line* which can be used to depict the mouth of the bend; the extent of the *bend region* (gray area in Fig. 2a) is enclosed by the bend segment and the base triangle *T*. The *trend line* is

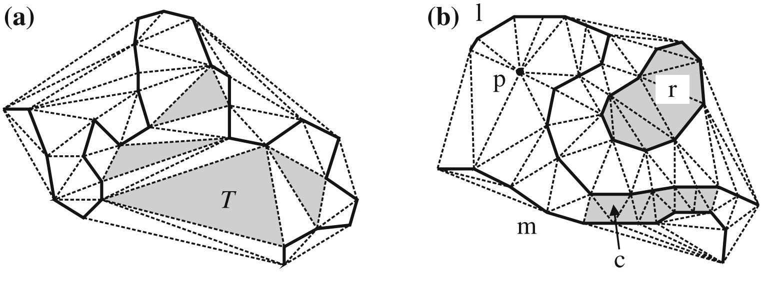

Fig. 1 Triangulation-based structure that supports structural knowledge **a** sub-region and shape description for a meandering line; **b** spatial relations and narrow region detection

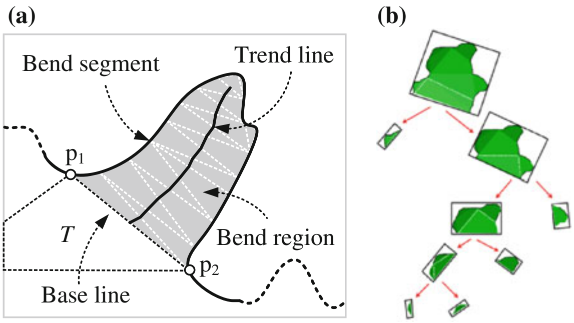

Fig. 2 The descriptors of bend structure (**a**), which can be used to describe the shape of micro bends at different levels of hierarchy (**b**)

derived through triangulating and skeletonizing (Zhang et al. 2008; Ai et al. 2014) the bend region. The trend line of a bend region reflects the main orientation of the bend region which can be measured by the trend line pointing from the base to the end of the bend region. Properties like compactness and elongation can be derived based on these descriptors. Note that with the hierarchical bend structure described in Ai et al. (2014), any bend in the structure can be characterized by these descriptors (Fig. 2b) so that we can find needed ones in the hierarchy.

Since the above-mentioned operations are not built-in functions in spatial databases, we implemented them as database extensions so that they can be used together with those built-in functions.

3.2 Formalizing Geographical Concepts with Description Logics

While there are many knowledge formalisms (e.g. frames, semantic networks, rules), we decided to use *Description Logics* (Baader et al. 2003) as knowledge formalism for the description of concepts and relationships in the geospatial domain. DLs provide abstract syntax, which forms the foundation of many ontology languages such as the Web Ontology Language (OWL[1]). Note that the abstract syntax of DLs is used in the paper for clarity and OWL, a concrete syntax of DLs, is employed for implementation purposes (see Sect. 4).

To understand the DL syntax used, we briefly introduce the basics of the syntax. The syntax consists of *concepts* (unary predicates), *roles* (binary relations) and restrictions on roles. A role links an individual in a domain to an individual or property in a range which is also called *role filler*. The following axioms (a.k.a TBox) show a possible description of knowledge in the spatial domain:

[1]http://www.w3.org/TR/owl-guide/.

$$\textbf{SpatialObject} \sqsubseteq_C \textit{TopConcept}(\top) \tag{1}$$

$$\textbf{SpatialRelation} \sqsubseteq_R \textit{SpatialObject} \times \textit{SpatialObject} \tag{2}$$

$$\textbf{Building} \sqsubseteq_C \textit{SpatialObject} \tag{3}$$

$$\textbf{hasNearbyNeighbor} \sqsubseteq_R \textit{SpatialRelation} \tag{4}$$

$$\textbf{ClusteredBuilding} \equiv_C \textit{Building} \sqcap (\geq 2 \ \textit{hasNearbyNeighbor.Building}) \tag{5}$$

Axiom (1) expresses that *SpatialObject* is subsumed by the top concept (which is never subsumed by other concepts), where $\sqsubseteq_C$ is the *concept subsumption* construct. Similarly, Axiom (2) describes a *role subsumption* ($\sqsubseteq_R$). The role *SpatialRelation* has a *domain*: *SpatialObject* and a *range*: *SpatialObject* (an object mapped to another object). Since *hasNearbyNeighbor* is subsumed by *SpatialRelation*, this implies the former inherits the domain and range of the latter. Axiom (5) describes the concept *ClusteredBuilding* with the *concept definition* construct ($\equiv_C$), expressing that a clustered building is a building which has at least two nearby neighbors. The statement also implies that *ClusteredBuilding* is subsumed by *Building*. The *intersection* construct ($\sqcap$) is used when composing a complex concept from different atomic ones. In Axiom (5), atomic concepts are *Building* and (≥ 2 *hasNearbyNeighbor.Building*). The latter statement can be seen as an *anonymous concept*, which restricts the intension of *ClusteredBuilding* in Axiom (5). In the *anonymous concept*, the *unqualified number restriction* construct ($\geq$) is used to specify the cardinality of the role: *hasNearbyNeighbor.Building*, meaning that each clustered building must have at least 2 nearby neighbors which are instances of *Building*.

Other constructs like the *role definition* ($\equiv_R$), the *existential quantifier* ($\exists$), the *universal quantifier* ($\forall$) and the *negation* ($\neg$) will also be used in the remaining sections to define high-level cartographic concepts and complex roles. Details of all notations, their semantics and interpretations refer to Baader et al. (2003).

3.2.1 Reasoning with Description Logics

DLs can be used to describe the knowledge bases (KB) for a concrete domain. A knowledge base consists of a set of terminological axioms (TBox) and a set of assertional axioms (ABox). A TBox forms a priori knowledge of the domain by defining concepts and their relations (e.g. Axioms (1)–(5)), while an ABox describes the known facts about the world. An example ABox may look like:

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Building(a)                        - concept assertion
hasNearbyNeighbor(a, b)            - role assertion
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where a, b are data instances, and the ABox asserts that a is a building and b is a's nearest neighborhood. Reasoning with KB is an important ability of DL systems. It can be used to infer implicit knowledge (semantics) hidden in TBoxes and ABoxes, and make them explicit (Baader et al. 2003). The inference capabilities that are concerned in this paper are *Realization* (i.e. finding the most specific concept of which an object is an instance) and *Retrieval* (i.e. finding all objects that are instances of a given concept).

The interpretation task can be viewed as a *realization* process, which aims at finding the most specific concept of which an individual is an instance (Möller and Neumann 2008). However, the interpretation of complex geo-concepts from spatial databases cannot be addressed simply based on the logic-based reasoning. Take the interpretation of *ClusteredBuilding* for example. If a, b, and c are asserted as instances of *Building* in an ABox, the *realization* will not work as the reasoner does not know the relation between the three objects. This therefore calls for a spatio-terminological reasoning.

3.3 Concept Interpretation as Reasoning Over Knowledge Bases

To address the spatial related reasoning problem, we adopt the notion of spatio-terminological reasoning to integrate spatial algorithms with logic-based automated reasoning process. However we implement the notion in a different way than Haarslev et al. (1994). In the alternative integration the spatial functionalities are loosely coupled with DL systems. The design is shown in Fig. 3.

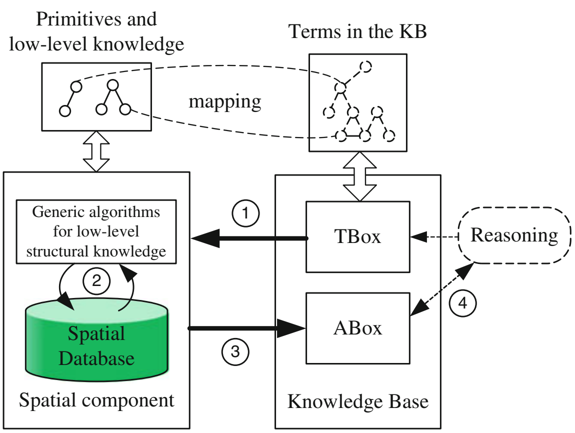

Fig. 3 The proposed design of spatio-terminological reasoning process

The spatio-terminological reasoning process in our design has two general components, namely the spatial component and the DL system (including a knowledge base and a reasoning engine). The basic idea of this spatio-terminological reasoning is to design a workflow to control the communication between the spatial component and the DL system to facilitate the automatic interpretation process. In Fig. 3 ‘Terms in the KB’ is directly connected to the TBox in the knowledge base. It represents the defined structures of any high-level concept of interest. ‘Spatial component’ consists of a spatial database and a set of generic operations (algorithms) to detect low-level structural knowledge. Here, we assume that the basic operations such as geometric, topological predicates and non-spatial queries are available in the spatial database. Hence the spatial component is sufficient to detect the low-level knowledge, including primitive entities, low-level properties and structural relationships. The vocabulary of the spatial component is marked by ‘Primitives and low-level knowledge’. The ‘Reasoning’ component is a standard reasoner which is responsible for the consistency of both the TBox and the ABox and other reasoning services.

The automated interpretation of a high-level concept is decomposed into four major steps (see also Fig. 3):

1. **Mapping**: all Parent Concepts (*PC*) which subsume the high-level concept, all Roles (*R*) and Role Fillers (*RF*) appeared in the axioms of the concept definition are firstly identified. Then *PC, R* and *RF* are mapped to the vocabulary provided by the spatial component. This results in a list of database concepts and spatial relationships needed for the next step;
2. **Spatial processing**: according to the list resulted from step (1), database objects that are instances of *PC* and *RF* are retrieved. Then, the identified spatial relationships are tested with spatial operations (either built-in predicates or enriched algorithms) between the objects belonging to *PC* and the objects belonging to *RF*. The test subjects are always the objects from *PC*. The number of object pairs for each testing can be reduced using the range in each role specified by DLs;
3. **Assertion**: all the retrieved database objects (*O*) in the last step are asserted as the instances of *PC* and *RF* and then added to the ABox. In the case of role assertion, the object pairs that pass the relationship testing in the last step are added to the ABox as new role assertions. After this, ABox becomes ABox’, which is well prepared for the *realization* step;
4. **Reasoning**: by *realization* service, the high-level concept (hidden semantics) is inferred automatically with the ABox’ and the TBox. The interpretation process is by then terminated.

Note that, step (1) and step (3) are the communications between spatial component and the DL system, whereas step (2) and step (4) are carried out within the spatial component and the DL system respectively.

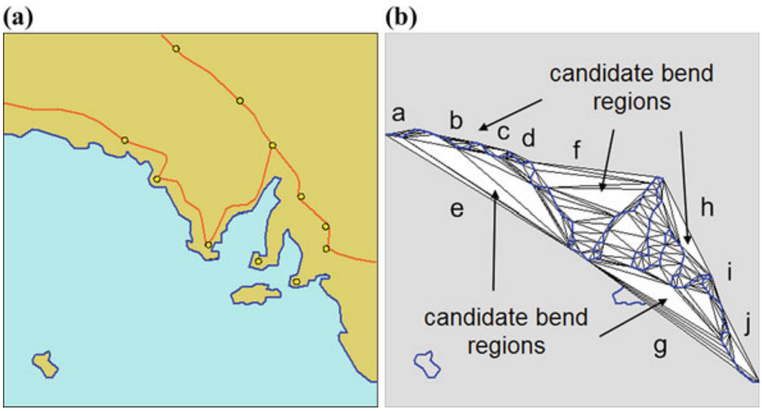

Fig. 4 **a** Example data set in Australia; **b** candidate bend regions generated for the interpretation task

4 Case Study: Interpreting Peninsulas from Spatial Databases

A prototype encompassing the spatial component and DL system was implemented to validate the proposed methodology. Besides the spatial operations available in the database, the generic algorithms that detect the proximity relationships, generate parts from wholes, and forming wholes from parts were implemented on top of a Delaunay triangulation (DT) based model. We used Pellet[2] as the underlying DL reasoner, which can be readily accessed by its OWL API.[3] The API was used for practical reasons: it enables programmers to define OWL-based knowledge bases (though they can be defined using an ontology editor like Protégé[4]), to access or modify concepts/roles axioms in a TBox, and to add known facts (e.g. *Sea(a), Neighbor(a, b)*) to or remove them from an ABox. Moreover, one can invoke almost all automated reasoning services available in the underlying reasoner via the API.

4.1 Setting the Scene

A simple test dataset of coastal area is depicted in Fig. 4a, where peninsulas, harbors, bays, mainland, island, sea, cities are visible to human beings on the map. People usually asks, e.g., which cities/places are inside a peninsula? Here peninsula is understood as a region with implicit boundaries. Therefore, features like peninsulas

[2]http://clarkparsia.com/pellet/.

[3]http://owlapi.sourceforge.net/.

[4]http://protege.stanford.edu/.

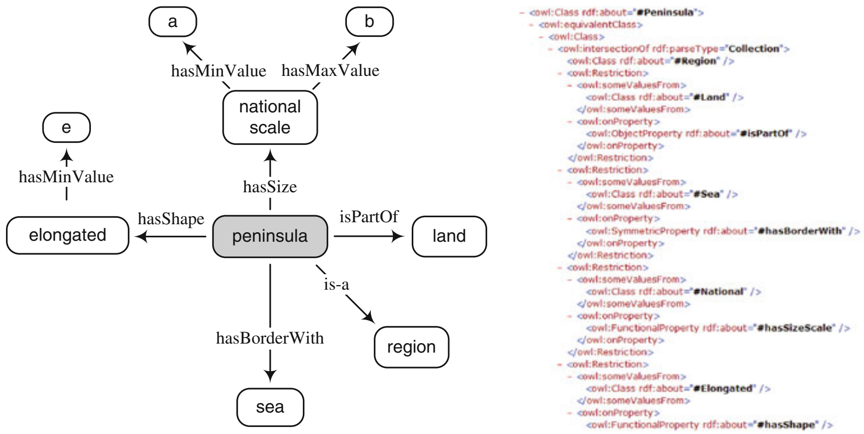

Fig. 5 A schematic diagram of the ontology of peninsulas (*left*) and its OWL description (*right*)

should be firstly retrieved before one can answer such questions. We applied the proposed method to identify instances of concepts like 'peninsula' and 'bay'.

4.2 Initializing the Knowledge Base

We first built up the initial TBox using Protégé and check its consistency. Atomic concepts in the case consist of *Region*, *Land*, *Island*, *Sea*, and *City*; complex ones include *Peninsula*, *Bay*, *CityInPeninsula*, and *OtherCity* which are formed based on the atomic concepts, attributes, and their relationships. Then, a mapping table was established so that the declared concepts can be linked to database classes and spatial operations. Finally, all the spatial objects in the database are added as initial known facts to the ABox. This is done by first searching the objects in the spatial database according to the classes appeared in the mapping table, and then add the identifiers of these objects to the ABox, using OWL API. Example assertions are *Sea*(*Austrilia_sea*) and *Land*(*Austrilia_land*).

Peninsula is defined based on explanations in Wikipedia[5]: "[…] it is a region, with shape and size restrictions, contained by land and sharing common boundary with sea." Figure 5 shows its ontology and OWL document.

As a proof-of-concept, '*Peninsula*' is defined in DLs in Listing (6). However, we are by no means to say that this is the only way to define peninsulas. For instance,

[5]http://en.wikipedia.org/wiki/List_of_peninsulas.

a peninsula needs not to be at the national scale. We add this constraint here only to demonstrate the formalism and the inference process.

$$\begin{aligned} \textbf{Peninsula} \equiv_C\ & \mathit{Region} \\ & \sqcap \exists \mathit{isPartOf.Land} \\ & \sqcap \exists \mathit{hasBorderWith.Sea} \\ & \sqcap \exists \mathit{hasShape.Elongated} \\ & \sqcap \exists \mathit{hasSize.NationalScale} \end{aligned} \tag{6}$$

4.2.1 Characterization of Peninsula Candidates

The inference starts by parsing the OWL document of *Peninsula* using the API. The program informs the spatial component that only one parent concept (i.e. *Region*) is needed for the subsequent reasoning. However, only '*Austrilia_sea'* and '*Austrilia_land*' regions are available in the database (Fig. 4a), which fail to pass the *isPartOf.Land* test. Therefore, we generated the candidate bend regions using the algorithm described in Sect. 3.1 and fed the detected sub-regions {*a, b, c, d, e, f, g, h, i, j*} (Fig. 4b) into the ABox.

After the high-level concept is formalized with DLs, the next step is the detection of the required low-level knowledge. The formal definition of Peninsula (Listing (6)) informs the spatial component that knowledge of topology, shape, and size are needed. The knowledge on these three concepts is detected as follows.

hasShape is characterized using Elongation ratio (i.e. length (trend line)/length (base line)) based on the bend descriptors introduced in Sect. 3.1. Two qualitative descriptors are derived here: *Elongated* (Elongation ratio $\geq$ 0.6) and *Flattened* (Elongation ratio < 0.6). These reflect only roughly the shape property of peninsulas as well as bays, rather than definitive values.

hasSize is determined by the size of bend region. Since the size of any peninsula in reality has a lower and an upper bound, *NationalScale,* a value restriction, is specified tentatively as size $\in [80, 250] \times 10^2$ km^2. Likewise, *Local*: [0, 20], *Regional*: [20, 80] and *Global*: [250, −] are specified as tentative values characterizing different sizes.

isPartOf and *hasBorderWith* were mapped to topological operations (e.g. contain and meet) in the spatial database. Such relationships are tested between the detected bend regions and other objects specified in the range of the relationships, and the new role assertions are formed (e.g. *isPartOf*(*e, Austrilia_sea*)).

After the above knowledge was tested for all bend regions and between the regions and other individuals, the asserted knowledge was added to the ABox via OWL API. Finally, the automated interpretation was launched by invoking the *realization* service in Pellet, also through the API. This process is fully automated. The size and shape values of all the candidate regions are displayed in Table 1.

Table 1 Characteristics (Char.) of the bend regions derived using the descriptors mentioned in Sect. 4.2.1 (L-Local; R-Regional; N-National; G-Global; E-Elongated; F-Flattened)

Instance	a	b	c	d	e	*f*	*g*	*h*	i	j
Size ($\times 10^2$ km^2)	5.7	9.6	11.7	3.8	554	*486*	*691*	*246*	15.6	72.8
Char.	L	L	L	L	G	*G*	*G*	*N*	L	R
Shape	0.2	0.5	0.4	0.4	0.3	*0.8*	*0.9*	*1.0*	0.6	0.3
Char.	F	F	F	F	F	*E*	*E*	*E*	E	F

4.2.2 Refined Results

The automated interpretation identifies *h* as the only peninsula from the candidate regions. This result is not very promising as we also observe other peninsulas in Fig. 4a. There are several reasons for the misinterpretations. First, the use of crisp condition such as *NationalScale* is too restrictive. Second, the inference did not make use of all bend regions detected at different levels of detail.

In this experiment, the inference made use of all bend regions in the hierarchy (using the technique in Ai et al. 2014). The inference traverses the hierarchy from the root until it finds the largest bend regions that satisfy conditions defined in Listing (6). Some bend regions that originally had branches are decomposed into separated bend regions (e.g. the bend g and h in Fig. 4b). The shape and size of these generated sub-regions are shown in Table 2 (some small bends are excluded for clarity). The refined result was more satisfactory. Regions $\{f1, h1, h2\}$ are now recognized as peninsulas and regions: $\{g1, g2\}$ are recognized as bays (bay differs from peninsula only in that it is part of sea and adjacent to land; its formal definition is not shown due to limited space). The results of automated interpretation are visualized in Fig. 6. As a consequence, the described interpretation task also identifies instances of *CityInPeninsula* and *OtherCity*.

To get more insight into the reasoning process we can look at different states of the knowledge base during the inference process (visualized in Fig. 7 Protégé with Ontoviz plug-in). For clarity, only *subsumption* and *instance-of* relationships are displayed.

Table 2 The characteristics of the sub-regions refined from regions f, g, and h

	f		g			h	
Instance[1]	f1	f2	g1	g2	g3	h1	h2
Size	187	12	223	81	106	96	54
Char.	N	L	N	N	N	N	R
Shape	0.9	0.7	2.3	1.9	0.5	2.6	0.9
Char.	E	E	E	E	F	E	E

[1]Instances obtained using hierarchical bend structure, listing only the changed instances

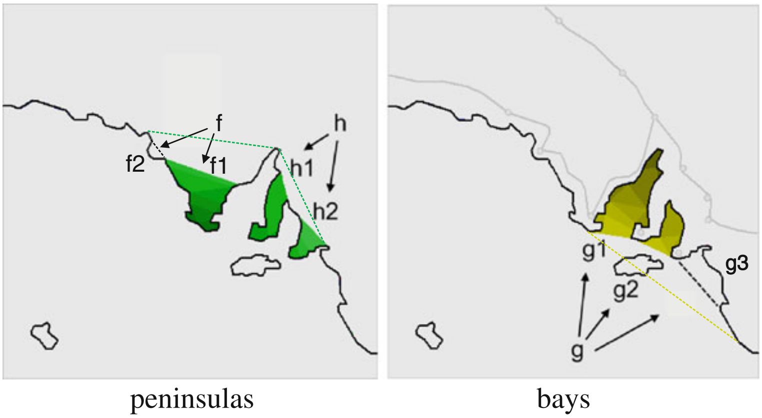

Fig. 6 Visualized results of the interpreted instances

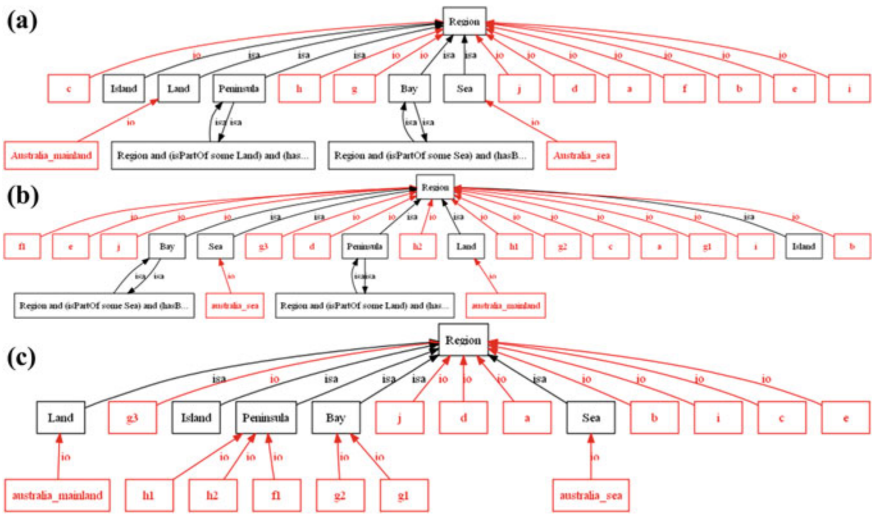

Fig. 7 Different states of the knowledge base ('isa'—subclass of; 'io'—instance of) **a** individuals and their asserted types in initial state; **b** the state after refinement to candidate bend regions; **c** the state after automated reasoning—most specific concepts of instances inferred

The bend regions are originally instances of the concept *Region*. After the *realization* process, some of them are inferred as instances of more specific concepts such as *Peninsula* and *Bay* (Fig. 7c).

5 Main Findings and Outlook

In this paper we proposed a method to automatically interpret complex geographical concepts from low-level knowledge. A practical spatio-terminological reasoning process was designed and implemented by enhancing existing DL reasoners with spatial functionalities. Combining the spatial and terminological components and applying them to the example of peninsula showed the potential of this methodology.

The use of *Description Logics* enables a more transparent modeling and better maintenance of spatial knowledge. A domain expert or knowledge engineer does not need to dive into the implementation level in order to revise the condition for inferring a different concept. The ultimate goal is that one can find a set of atomic spatial operations that are reusable and composable in flexible ways, so that query over any complex geographic concept can be achieved by chaining those atomic operations and primitive facts, as described in the knowledge base. But the harder question is whether there exists such a set of atomic spatial operations, and how to semantically annotate the operations such that they can be found and matched to foster a fully automated inference process. Further research along this line of thought should also contribute to the endeavor of semantic web and service chaining. In addition, future work will see how the proposed approach performs with real world datasets.

In addition, the proposed method does not consider the uncertainty in the knowledge modeling process. Uncertainty is unavoidable even in our toy example, where crisp thresholds, such as shape (*Elongated*) and size (*NationalScale*) in the peninsula case, are limiting factors and should be address in the future. We have to adopt the workaround because the inference tools available to us at the moment were not capable of making uncertainty reasoning.

In the past few years, there are many proposals that aim to extend DLs to be able to handle uncertainty (Haarslev et al. 2006). The uncertainty can be handled at the language, knowledge base, and reasoning levels. The underlying reasoning model can be based on Fuzzy logic, probabilistic theory or others (Baader et al. 2003; Haarslev et al. 2006). This trend is also taken by the W3C working group on uncertainty reasoning,[6] and may become the foundation for the next generation web (semantic web). Although uncertainty reasoning using DLs has been proposed in recent years (e.g. Carvalho et al. 2010), there is still a lack of tools for practical use. Upon the perfection of such inference techniques, geospatial information retrieval would benefit most from it as geographic concepts are inherently vague.

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[6]http://www.w3.org/2005/Incubator/urw3/XGR-urw3-20080331/.

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