From Polygons and Timestamps to Dynamic Geographic Features: Grounding a Spatio-temporal Geo-ontology

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Abstract. This paper presents a knowledge representation approach to modelling and manipulating spatio-temporal data and to grounding a spatio-temporal geographic ontology upon the data. This approach has been developed in the form of a definition-based ontological framework, upon which GIS applications can be developed to perform analysis of geographic phenomena by querying the spatio-temporal database in a more conceptualised fashion. We draw special attention to the representation of geographic features which can change over time, since an appropriate modelling of these dynamic features can provide a natural way of defining other dynamic entities of geographic space, such as events and processes. In addition, the paper discusses some architectural aspects of a GIS which incorporates our semantic model and describes an example of event modelling to illustrate the application of the proposed approach.

Keywords: Spatio-temporal Data Modelling, Geographic Ontologies, Ontology Grounding, Spatio-temporal Reasoning.

1 Introduction

Researchers in Geographic Information Science (GIScience) have investigated means of providing more conceptualised methods of manipulating and querying spatio-temporal data. Recent developments include conceptual models for spatio-temporal data (e.g., [9]), which are frequently described using the entity-relationship model (ER) and Unified Modelling Language (UML). However, despite their expressiveness for describing real-world entities, they lack in providing a method of linking the conceptual and data layers so that reasoning is allowed on spatio-temporal data. Object-oriented approaches have also become of interest (e.g., [12]), since they can provide a model which is both concrete (i.e., implemented in software) and described in a more conceptualised fashion. Nonetheless, inference capabilities of these models are still limited, and consequently queries tend to become more complex and less expressive.

In parallel with this, the scientific community has increasingly realised the value of knowledge representation and reasoning (KRR) approaches to the development of modern GIS. In GIScience, ontologies have been proposed for a

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variety of purposes; however, the ontology level has been traditionally developed separately from the data level. In this conventional way of designing ontology-based systems, reasoning on queries is performed within the ontology, and data that matches these queries are returned. As a result, the data context can be disconnected from the ontology, which can bring significant limitations to the modelling of dynamic elements of geographic space. We assume that data is a faithful reproduction of physical elements of the world and therefore should be considered to derive coherent descriptions of conceptual entities which are related to these elements.

'*Grounding* gives meaning to ontological primitives by relating them to qualities outside the symbol system, and thus stopping infinite regress' [11, p.01]. Approaches to grounding geographic ontologies have been already proposed. For instance, Bennett et al. [2] presented an approach to grounding vague geographic terms (e.g., river, lake) based on geometric characteristics of water bodies (e.g., linearity, expansiveness). Scheider et al. [11] suggested to ground symbols for qualities (e.g., depth of a lake) by defining them from perceptual/observable primitives (e.g., 'length of a vertically aligned path from the water surface to the bed of a particular water body' [11, p.02]). In the context of this work, we consider that the ontology grounding is established not only when primitive symbols are linked explicitly to elements of data, but also when higher level concepts can be defined in terms of these primitive ones, that is, without concerns about the data structure. For instance, primitive symbols for 'proximity' could be grounded upon a dataset consisting of geographic points (pairs of coordinates) so that higher level concepts, such as 'neighborhood', could be defined without any reference to geographic coordinates.

Considering the temporal dimension (i.e., assuming that qualities of geographic elements are subject to change over time) adds significant challenges to the grounding problem. One might argue that the grounding of temporal information is realised by mapping symbols such as 'instant' or 'interval' to timestamps at the data level. Nonetheless, although this provides a explicit link between the ontology and data levels, we demonstrate that it is not sufficient to make a definite separation between the ontology and the data structure. Methods of grounding geographic ontologies upon the data have been already proposed, however approaches to developing an ontology grounded upon spatio-temporal data seem not to have been sufficiently discussed in the literature, and therefore further developments are required.

This paper presents a KRR approach to representing the spatio-temporal geographic data and to grounding a spatio-temporal geographic ontology upon the data. The discussion given in this paper pays special attention to the representation of *geographic features* which can change over time, as an appropriate modelling of these dynamic features can provide a natural way of defining other dynamic entities of geographic space, such as events and processes. For instance, by understanding the way a forest evolves, one can provide means of identifying events and processes associated with deforestation phenomena. The representation of events and processes is a complex field and is still the subject of substantial disagreements in the literature. Therefore, a discussion on approaches to representing these conceptual entities is beyond the scope of this paper[1]. However, we present an example of event modelling to illustrate the application of the approach proposed here.

The remainder of this paper is structured as follows. The next section overviews some architectural aspects of a GIS which incorporates our semantic model. Following this, Section 3 describes our approach to modelling spatio-temporal data. Then Section 4 presents our approach to representing dynamic geographic features. This is followed by a discussion, in Section 5, on the representation of other dynamic entities in terms of changes affecting geographic features. Finally, Section 6 concludes the paper and points to future directions.

2 Main Architecture

This section describes a typical architecture of a GIS which incorporates our model for representing dynamic geographic entities. This is illustrated in Figure 1. In this architecture, the communication between the *GIS server* and the *data layer* can be established through an *interpretation layer*, which performs logical queries specified in terms of conceptual elements of a *spatio-temporal geographic ontology*. Moreover, the GIS Server can access the spatial-temporal data in the conventional way (i.e., by accessing directly a DBMS or a shapefile), so that map layers generated by these different forms can be overlayed, which is useful to conduct certain analysis. We have built a system prototype to reason about geographic events and processes which adopts this architecture. In this prototype, the components of the interpretation and grounding layers have been developed in SWI-Prolog, whilst the data is stored in a PostgreSQL database.

A *grounding mechanism* provides a way to link explicitly the spatio-temporal geographic ontology and the *spatio-temporal data*, and specific algorithms are applied to ground particular elements of the ontology. Geometric computations required by these algorithms are performed by the *geometry processor*, which contains ad-hoc implementations of geometric operations and also reuse built-in spatial functions provided by a spatial DBMS. The spatio-temporal data may come from heterogeneous sources and therefore may be provided in distinct formats and may have different internal structures. Hence these *raw data* are processed by a designated *data converter*, which converts the data to the format (STAR data model) required by the grounding mechanism.

3 Spatio-temporal Data Representation

Existing spatio-temporal models commonly assume that the *material objects*[2] which inhabit the model are spatially well defined in the data (e.g., a desert

[1] For a comprehensive review of issues and challenges for representing geographic processes, see [4]. For approaches to modelling geographic events and processes see [3,5].

[2] In the context of this paper, such objects are geographic features.

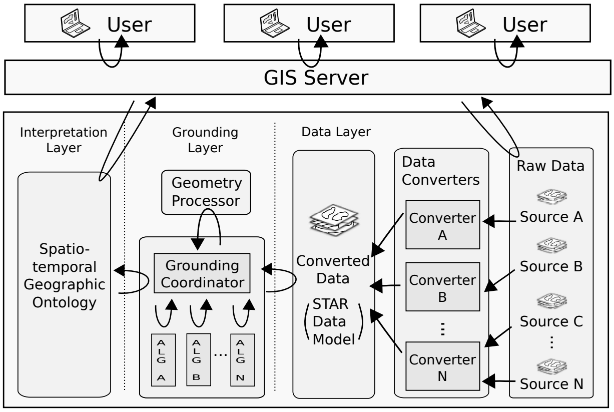

Fig. 1. Typical GIS architecture augmented with our logic-based data model and ontology grounding mechanism

represented as a precise polygon). However, geographic data can be provided in other forms, such as *fields*, which are "measurements on a variable whose value varies through geographic space" [8, p.222]. In this case, as suggested by Galton [7], objects can be inferred from fields (e.g., a desert could be determined from data about precipitation rate).

Our approach to representing the spatio-temporal data aims to provide representational flexibility, so that a wide range of elements can be identified by inferences performed upon a very simple and uniform snapshot-based storage structure. This is also a powerful resource for integration of data originated from distinct sources and at different temporal granularities. This method allows implicit data to be derived and the semantics of time-dependent concepts to be maintained concise thorough continued updates in the database. Furthermore, this approach aims to facilitate the grounding of ontological concepts representing dynamic elements of reality.

The formalism presented in this paper is described in terms of definitions in first-order logic, where free variables are implicitly universally quantified with maximal scope. We employ the Region Connection Calculus (RCC) [10] as the theory of *space*[3]. We assume a total linear reflexive ordering on *time*, and use explicit variables t_i and i_i denoting time instants and intervals, respectively. Time instants variables can be compared by ordering ($\prec$ and $\preceq$) operators and can be quantified over in the usual way ($\forall t[\phi(t)]$). We use the functions $\mathsf{begin}(i)$ and $\mathsf{end}(i)$, which return an instant corresponding to the beginning and the end of an interval i, respectively. The Allen's [1] temporal relations are also employed[4]. We also define the relation $\mathsf{In}(t, i)$ between intervals[5]. The propositional construct $\mathsf{Holds\text{-}On}(\varphi, i)$ asserts that formula φ is true at every time instant t where $\mathsf{In}(t, i)$

[3] The relations *connected* $\mathsf{C}(r_1, r_2)$ and *equals* $\mathsf{EQ}(r_1, r_2)$ are mentioned in this paper.
[4] The relations *partially overlaps* $\mathsf{PO}(i_1, i_2)$ and $\mathsf{Meets}(i_1, i_2)$ are mentioned here.
[5] $\mathsf{In}(i_1, i_2) \equiv_{def} \mathsf{Starts}(i_1, i_2) \vee \mathsf{During}(i_1, i_2) \vee \mathsf{Finishes}(i_1, i_2) \vee \mathsf{Equals}(i_1, i_2)$

holds. The function $\mathsf{ext}(f)$ is also employed, which returns the spatial region corresponding to the spatial extension of a feature f.

3.1 Spatio-temporal Attributed Regions

Our logic-based approach to modelling spatio-temporal data has been named *STAR Data Model* (which stands for Spatio-temporal Attributed Regions). In this model, the spatio-temporal data are stored as triples of the form $\langle a,\ g,\ s\rangle$, which corresponds to the fact that attribute a holds for geometry[6] g at time instant denoted by timestamp s. A broad range of attributes can be associated with geometries. They can be used to describe either types of region coverage[7] (e.g., 'forested', 'arid', 'water covered') or types of geographic features (e.g., 'ocean', 'desert', 'forest'). Polygons denote either spatial regions or spatial extensions of geographic features. Those triples are represented at the logical level as facts of the knowledge base by using the predicate *Spatio-temporal Attributed Region* $\mathsf{Star}(a, g, s)$. The following sortal predicates are also employed to denote four different types of attributes:

– $\mathsf{CAtt\text{-}Hom}(x)$ and $\mathsf{CAtt\text{-}Het}(x)$ are applied, respectively, to denote *homogeneous* and *heterogeneous coverages*. These attributes are associated with spatial regions which are regarded as covered by a single or multiple types of coverages, respectively. Examples of homogeneous coverages are 'forested', 'arid', 'water covered' and 'precipitation $<$ 250mm'. Examples of heterogeneous coverages are 'urbanised' and 'agricultural'.
– $\mathsf{FAtt\text{-}Sim}(x)$ and $\mathsf{FAtt\text{-}Com}(x)$ are applied, respectively, to denote *simple* and *compound geographic features*. While simple features (e.g. desert, road, sea) cannot be composed by other features and every region which is part of them must have the same coverage, compound features (e.g., city, park, beach) may contain other features or spatial regions with different coverages.

The actual denotation employed by these distinct types of attributes depends on the intended application. For example, an attribute named 'forested' can be employed to denote either a homogeneous or a heterogeneous type of coverage. The former might be applied when different types of vegetations are not relevant to the problem at hand, whilst the latter might be employed in association with several homogeneous coverage attributes denoting types of vegetation.

The spatial extension of a geographic feature at a certain time instant can be asserted explicitly or can be inferred as the maximal well-connected region[8] of some particular coverage. *Stars* facts associated with feature attributes can

[6] In the current version of our implementation, geometries are restricted to 2-dimensional simple polygons, which are those whose boundary does not cross itself.

[7] A type of *region coverage* is *not* restricted to types of land coverages. This can also denote *qualities* which can be measured (e.g., by sensors or human observation) and associated with a certain portion of the earth surface, such as 'hot' or 'arid'.

[8] The term 'well-connected region' is used here in agreement with the discussion and definitions given in [6].

be asserted explicitly when the original dataset contains such data. Moreover, certain inferred *Stars* representing spatial extensions of features are asserted explicitly by the system for performance improvement purposes.

Apart from the facts asserted using the predicate *Star*, other facts can also be asserted using the predicates *Can be Part* $\mathsf{CP}(a_1, a_2)$ and *Must be Part* $\mathsf{MP}(a_1, a_2)$ to determine, respectively, that part-hood relations *can* or *must* hold between *Stars* associated with attributes a_1 and a_2 (e.g. $\mathsf{CP}(paved, urbanised)$, $\mathsf{MP}(built\text{-}up, urbanised)$). Additionally, facts can be asserted using the predicate *Cannot Intersect* $\mathsf{NI}(a_1, a_2)$, which ensures that spatial regions associated with attributes a_1 and a_2 never overlap (e.g. $\mathsf{NI}(urbanised, forested)$). This predicate is useful to support inferences of spatial boundaries between distinct heterogeneous regions as well as inferences of holes affecting geographic features. In addition, a set of axioms is specified to determine inference rules for deriving implicit data and to specify data storage constraints[9].

A formal model $\mathfrak{G}$ of a geographic dataset is $\mathfrak{G} = \langle \mathbb{R}^2, \langle T, \trianglelefteq \rangle, A, \mathcal{D} \rangle$, where: $\mathbb{R}^2$ is the real plane, which represents a portion of the earth's surface under some specified projection[10]. T is the set of all time instants over the time sequence $\langle T, \trianglelefteq \rangle$, where $\trianglelefteq$ is a total linear order over T. A is a set of geographic attributes. $\mathcal{D} \subseteq A \times \mathsf{Poly}(\mathbb{R}^2) \times T$ represents the geographic attributed data as a subset of all possible triples of the form $\langle a,\ g,\ s \rangle$, where $\mathsf{Poly}(\mathbb{R}^2)$ is the set of 2-dimensional simple polygons over $\mathbb{R}^2$. In this paper, we do not intend to present an extensive description of our data representation model, and therefore the full axiomatisation is not given. Rather, we give an informal overview on some key inference rules present in the model. These are as follows.

A. If at a time instant t two spatial regions r_1 and r_2 with the same coverage are spatially connected, then there exists a spatial region which corresponds to their spatial union and has the same coverage of r_1 and r_2 at t.
B. Given two spatial regions r_1 and r_2 with distinct coverages a_1 and a_2, if these regions are spatially connected at a time instant t and there exists a type of coverage a_3 which can comprise the coverage(s) denoted by a_1 and a_2, then the region representing the spatial union of r_1 and r_2 is said to be covered by a_3 at t.
C. Given a spatial region r covered by a at a time instant t, if there exists *no* region r' which at time t contains r and is also covered by a (or covered by a', in case a is a heterogeneous type of coverage and a' is one of the homogeneous coverages which can be present in a), then r denotes the spatial extension of a geographic feature at time t (i.e., a geographic feature is regarded as the maximal well-connected region of some particular coverage).
D. Given a spatial region r covered homogeneously by a, every sub-region of r is also a region with the same coverage of r.

[9] Storage constraints ensure semantic consistency within a dataset (e.g., a heterogeneous region cannot be part of a homogeneous region at a given time instant).

[10] Clearly, one might want to use a different coordinate system or a 2.5D surface model. For simplicity we just assume that the space is modelled by $\mathbb{R}^2$; however, this could easily be changed without modification to the rest of the semantics.

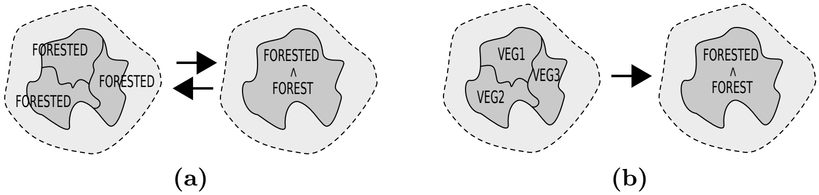

Fig. 2. Examples of inferences involving attributed spatial regions

E. Given a geographic feature f, there exists a spatial region r with the same spatial extension of f (i.e. $r = \mathsf{ext}(f)$).

Figure 2a illustrates the spatial extension (at a certain time instant) of a simple geographic feature of type 'forest' which has been inferred from 'forested' spatial regions by applying rule (A) then (C). Note that an inference could have been made in the opposite direction by applying (E) then (D). On the other hand, in Figure 2b, 'forest' is regarded as a compound geographic feature and its spatial extension (at a certain time instant) has been inferred by applying (B) then (C). Note that, in this case, the inference could not have been made in the opposite direction.

4 Modelling Geographic Features

We are particularly interested in geographic features which can be modelled as the maximal well-connected regions of some particular coverage. Examples are forests (which can be regarded as the maximum extension of a certain type of vegetation) and deserts (which can be defined based on the level of precipitation). Geographic features are regarded as the material objects which inhabit our spatio-temporal model. They are discrete individuals with well-defined spatial-temporal extensions, are wholly present at any moment of its existence and can change some of their parts while keeping their identity (e.g., a forest can be partially deforested while being still the same forest). Their *identity criteria* is defined in terms of connectivity of their spatial extension over a time interval. We define the operator $f_1 \risingdotseq f_2$, which is true if f_1 and f_2 are geographic features which have the same identity criteria (i.e. f_1 and f_2 are the same individuals).

$$f_1 \risingdotseq f_2 \equiv_{def} \exists i[\forall i_1 i_2[\mathsf{In}(i_1, i) \wedge \mathsf{In}(i_2, i) \wedge (\mathsf{PO}(i_1, i_2) \vee \mathsf{Meets}(i_1, i_2)) \wedge \mathsf{Holds\text{-}On}(\mathsf{EQ}(\mathsf{ext}(f_1), r_1), i_1) \wedge \mathsf{Holds\text{-}On}(\mathsf{EQ}(\mathsf{ext}(f_2), r_2), i_2) \rightarrow \mathsf{C}(r_1, r_2)]]$$

The *maximum interval* on which a feature maintains its identity is regarded as the interval on which the feature exists (i.e., it is 'alive'). A *feature's life* is modelled as a sequence of *Minimum Life Parts* (MLP), which are the shortest stretches of the life-time within which the feature's spatial extensions are known. In other words, an MLP is a pair of the form $\langle \mathsf{Star}(a, g_1, s_1), \mathsf{Star}(a, g_2, s_2) \rangle$, representing consecutive snapshots of an individual feature. These *Stars* are associated with the same feature attribute a, and can be either asserted explicitly or resulting from inferences performed involving other *Star* (as shown in Figure

2). Figure 3a illustrates the spatial extensions of a feature represented by 7 *Stars*. On the other hand, in Figure 3b, the feature is shown as a spatio-temporal volume, representing an object which occupies a portion of geographic space at any instant of its existence.

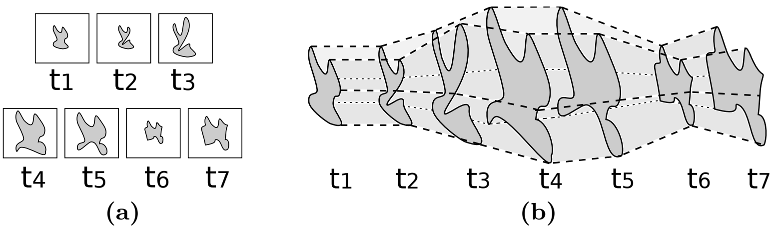

Fig. 3. In (a), the spatial extension of a geographic feature appears in different snapshots; In (b), the feature is shown as a spatio-temporal volume.

Once the concepts *feature*, *feature life*, and *minimum life part* are defined, higher level concepts describing dynamic geographic entities (e.g., events and processes) can be defined in terms of them, that is, without the need to refer to lower level concepts (i.e. *Stars*). This makes the ontology clearly independent from the data structure. The explicit link between the ontology and data levels is established by the definition of an MLP, which is given in terms of *Stars*. The relation $\mathsf{MLP}(f, r_b, t_b, r_e, t_e)$ is specified below, where f, r, t are variables of our logical language denoting, respectively, features, feature types, spatial regions and time instants. This language also includes a set of assignment functions which map variables of the vocabulary to elements of the domain (r_i are assigned to geometries, t_i are assigned to timestamps and u_i are assigned to feature attributes. This relation is defined as follows.

$$\begin{aligned}&\mathsf{MLP}(f, r_b, t_b, r_e, t_e) \equiv_{def} \exists u, r_b, t_b, r_e, t_e[u = \mathsf{feature\text{-}type}(f)\\ &\quad \mathsf{Star}(u, r_b, t_b) \wedge \mathsf{Star}(u, r_e, t_e) \wedge t_b \prec t_e \wedge \mathsf{C}(r_b, r_e)] \wedge\\ &\quad \neg\exists r', t'[(t_b \prec t' \prec t_e) \wedge \mathsf{C}(r', r_b) \wedge \mathsf{Star}(u, r', t')]\end{aligned}$$

5 Modelling Dynamic Geographic Elements

The approach presented to modelling geographic features can be applied to support the representation of a variety of dynamic geographic elements. To illustrate, we describe an example where an *event* occurrence is defined in terms of spatial changes affecting a geographic feature and how the meaning of conceptual entities can be dynamically adapted to changes in the dataset. First, we define a logical relation *Expands* which compares the area of two spatial regions. This is as follows.

$$\mathsf{Expands}(r_1, r_2) \equiv_{def} \mathsf{area}(r_2) > \mathsf{area}(r_1)$$

Then the following predicate is defined to denote occurrences of expansion events affecting a geographic feature f over a time interval i. For simplicity, we omitted the case where the event occurs in the beginning or in the end of of a feature life.

$$\begin{aligned}&\mathsf{Occurs\text{-}On}(expansion, f, i) \equiv_{def} \exists r_{1b} r_{1e} r_{2b} r_{2e} t_{1b} t_{1e} t_{2b} t_{2e} [\\ &\quad \mathsf{MLP}(f, r_{1b}, t_{1b}, r_{1e}, t_{1e}) \wedge \mathsf{MLP}(f, r_{2b}, t_{2b}, r_{2e}, t_{2e}) \wedge (t_{1e} \prec t_{2b}) \wedge \\ &\quad \neg\mathsf{Expands}(r_{1b}, r_{1e}) \wedge \neg\mathsf{Expands}(r_{2b}, r_{2e}) \wedge \forall r_b r_e t_b t_e [\\ &\quad \mathsf{MLP}(f, r_b, t_b, r_e, t_e) \wedge (t_{1e} \preceq t_b \preceq t_e \preceq t_{2b}) \rightarrow \mathsf{Expands}(r_b, r_e)]]\end{aligned}$$

Observe that the predicate *Star* is not referred to at this level, which makes the definition clearly independent from the data structure. However, a concrete link between the data and logical layers is still maintained, so that changes in data reflects directly the meaning of conceptual elements.

To illustrate how this concrete link is established, suppose a dataset containing 7 *Stars*: $\mathsf{Star}(a, g1, s1)$, $\mathsf{Star}(a, g2, s2)$, ..., $\mathsf{Star}(a, g7, s7)$, where $s_1 \prec s_2 \prec s_3 \prec s_4 \prec s_5 \prec s_6 \prec s_7$ and $\mathsf{area}(g_1) = \mathsf{area}(g_2) < \mathsf{area}(g_3) < \mathsf{area}(g_4) = \mathsf{area}(g_5) > \mathsf{area}(g_6) < \mathsf{area}(g_7)$. Suppose that these elements meet the identity criteria of a feature so that a feature f is inferred, whose life is regarded as composed by 6 MLPs (as shown in Figure 3b). As $\mathsf{area}(g_1) = \mathsf{area}(g_2)$, the area occupied by the feature throughout the first part of its life is said to remain unchanged, and therefore the feature does not expand on this period. On the other hand, the feature is said to expand throughout the second and third MLPs. Given that, the proposition $Occurs(expansion, f, i)$, where $begin(i) = s_2 \wedge end(i) = s_4$, holds. That is, an expansion event is said to occur on the interval comprising the second and third MLPs of the feature f.

Now suppose that some additional data originating from a different source have been integrated into the dataset. These additional data include the element $\mathsf{Star}(a, g_\alpha, s_\alpha)$, which is chronologically positioned between the second and third elements of the original dataset. As a result, a feature f' is inferred (Figure 4), which is said to consist of 7 MLPs rather than 6. Moreover, the period before the event occurrence, on which the feature is said to remain unchanged is now longer, comprising the first 2 MLPs of f. Consequently, the proposition $Occurs(expansion, f', i)$ is false, as the interval on which the feature is said to expand has changed.

From the example given, it can be noticed that, as additional data are integrated into the dataset, an improved (i.e., more detailed) representation of reality is provided at the ontological level. Obviously, the example only illustrates one of numerous ways in which the spatio-temporal dataset may change and the

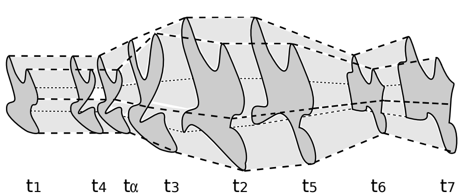

Fig. 4. Geographic feature after inserting a new snapshot into the dataset

variations in the meaning of conceptual entities are dynamically accommodated within the ontology.

6 Conclusion and Further Works

This paper presented a KRR approach to modelling spatio-temporal data and to grounding a spatio-temporal geo-ontology upon the data. It has been shown that modelling the spatio-temporal data in a logical fashion allows us to derive implicit data and provides a natural way to link the data and ontology layers, in order to enable reasoning about dynamic geographic elements. We consider this work as a significant step towards a more concrete integration between conceptualisation and real-world applications in GIS. Further developments include the modelling of additional geometric elements besides polygons, a more complex modelling of a feature life (comprising the modelling of possibles splits and merges), and the extension of the model to a 3-dimensional view of space.

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