Mapping between dynamic ontologies in support of geospatial data integration for disaster management

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Abstract

The effective management of disasters requires providing relevant and right information to the concerned decision makers. By its nature, disaster management involves multiple actors and organizations, potentially implying a significant volume of geospatial data coming from heterogeneous and autonomous geospatial data sources. Integration of these data sources is difficult not only because of the semantic heterogeneity of data but also because of the dynamic nature of the reality that is studied. The dynamic aspect of the reality has a direct impact in the conceptualisation of such a reality by adding different event categories to the domain ontology, thus making more complicated to apply existing methods for the mapping and integration of ontologies. In this article, we highlight some problems of heterogeneity that complicate the integration of ontologies composed of objects and events concepts; we also propose a similarity model designed to support mapping of these ontologies.

Keywords: Disaster Management, Semantic Integration, Geospatial Events, Dynamic Ontology, Semantic Similarity.

1 Introduction

In disaster management, analysts and decision-makers have to exploit large and complex geospatial data sources, and integrate them to obtain new information and knowledge. These data are produced in different domains for different purposes and in different contexts. However, the context of use of this knowledge is often implicit, so an important part of the knowledge is not understandable for users from other domains. This problem leads to semantic heterogeneity among geospatial data sources. Semantic heterogeneity occurs when the same real world concept has different abstract representations in different data sources. Kashyap and Sheth (2000) define semantics to be *"the scientific study of the relations between signs and symbols and what they denote or mean."* Semantic heterogeneities arise from divergences in meanings of the concepts, different paradigms or perspectives, incompatible constraints and assumptions. That is, the same concepts are interpreted differently (Park and Ram 2004). Consequently, there is an important need for developing models that can support the representation and sharing of different meanings carried by knowledge produced and stored in multiple geospatial data sources. Fortunately, there is an increasing consideration for semantic approaches in order to allow reasoning on meaning of data that are being exchanged between multiple geospatial data sources. Some of the most notable aspects of semantic approaches are the development of ontologies and semantic annotation of data (Arpinar et al. 2006), that is, the semantic enrichment of data with metadata. These approaches aim at developing formal top-down knowledge that captures aspects of meaning of data relating to domains of discourse (Fonseca et al. 2002). Using ontologies and metadata, knowledge can be re-contextualized in order to highlight similarities and dissimilarities in their meaning and representations in the different domains of application.

However, the way we perceive the real world is not static and the ontologies that support this perception need to be able to represent changes that happen in the real world. For example, in an airport system, new airplanes always appear, and change their status to the control tower. These changes can be represented explicitly in dynamic ontology. An event may be defined as an obvious change of important features which we are interested in (Howarth and Buxton 2000). A dynamic ontology can be used to describe the occurrence of different activities, schedules, and sensing events (Chen et al. 2004). Modifications of geospatial objects of reality or modifications of their status may be represented by events. This new temporal paradigm for representing entities of the real world brings new types of semantic, spatial and temporal heterogeneities which create more obstacles to the integration of multiples ontologies composed of concepts that represent either objects or events, or both. This paper is an attempt to bridge between ontologies which are composed of geospatial object concepts and event concepts. In this article we propose a semantic similarity mapping model that will help to reason on thematic, spatial and temporal similarities between concepts of those ontologies, and we define resolution rules and mapping strategies for relating these concepts in order to achieve semantic integration of ontologies of geospatial object and event concepts. We also argue that such a similarity model will needs to give qualitative and quantitative indication of the relation between concepts in order to help users to better mitigate information from different sources in an effective way.

The content of this article is structured as follows: first, we will present the background and related works on semantics and spatiotemporal properties of geospatial phenomena. In the third section, we will present our approach and identify heterogeneities that may arise between ontologies representing geospatial objects and events. In the fourth section we will present our model for mapping object and event concepts of different ontologies, with resolution rules for conflicts and mapping strategies in order to reason on similarity relations among object and event concepts. Finally in section 5 we conclude this paper and give future works.

2 Background and Related Works

2.1 Semantics

Recent advances in the information and communication technologies have made available a huge amount of data to analysts and decision makers for disaster management and other applications. Fast and effective mitigation of data from different sources requires semantic interoperability between these data sources. One of the important elements to be considered for semantic interoperability between information systems is the semantic of the information. Hence, semantic approaches are required for reasoning on meaning of data that are being exchanged between different systems. Ontologies support several semantic approaches such as semantic integration of multiple systems, semantic search (Helfin and Hendler 2003), semantic analysis and data discovery (Sheth et al. 2003). For semantic integration of heterogeneous systems, ontologies are used to describe the context of use of the data. However, ontologies are also heterogeneous, since they often differ according to their level of abstraction, their terminology, their structure, the definition of concepts, etc. In this case, the semantic integration of ontologies is a necessary condition to semantic interoperability (Klein 2001). The goal of semantic interoperability is to create a semantically compatible information environment based on the similar concepts between different domains (Park and Ram 2004). The integration of ontologies, that aim at reconciliating two or more heterogeneous ontologies, can be carried out by mapping, alignment or fusion of ontologies, these processes represent increasing degrees of integration of ontologies. The mapping of ontologies consists in identifying a formal expression which describes the semantic relation between two entities belonging to different ontologies (Bouquet and al., 2005). Consequently, the mapping of ontologies is closely related to the concept of semantic similarity. Many approaches for mapping between ontologies have proposed semantic similarity models to relate concepts. Models of similarity are based on different aspects of concepts being compared; they can compare similarity between names of concepts or between their descriptions with metrics such as *edit distance* (Giunchiglia and Yatskevich 2004) The semantic similarity can also be evaluated by comparing the common and exclusive properties of concepts according to the ratio model (Rodriguez and Egenhofer 2003), or using graph-based techniques, which consists in comparing the positions of entities in their respective graphs (Rada and al. 1989; Madhavan and al. 2001) or similar relations between concepts (Maedche and Staab 2002). Methods of mapping combining several aspects of concepts, such as properties, neighbourhood and position of concepts in the graph of ontologies, are also proposed for the evolution problem to relate schemas of multidimensional geospatial databases produced at different time (Bakillah et al. 2006). Semantic relations between concepts can also be established by means of geosemantic proximity predicates (Brodeur 2004), in order to identify the nature of the relation between geo-concepts, such as overlap, inclusion, equivalence, etc., by analogy with the topological relations identified by Egenhofer (1994). Qualitative relation between concepts such as identified in this last approach is very important to established mapping relation since it convey more semantic meaning than a quantitative relation that only gives the degree of semantic similarity but does not inform on the nature of the relation. However, much of the recent research in ontology mapping presented until now are focussed on essentially static ontologies. Reality described by geospatial phenomena such as in a natural disaster evolves in time and space. Consequently, besides semantic aspects, in disaster management, spatiotemporal properties of phenomena represented in ontologies are of major importance since it is recognized that geospatial data, which are described by thematic, spatial and temporal properties, are necessary in order to achieve efficient management of disasters (Cutter at al., 2003).

2.2 Spatiotemporal Properties of Geospatial Phenomena

If analysis of spatial data is often based on quantitative measurements, it is often needed to reason on semantic of geospatial data to help in geographical knowledge discovery. Semantic of geospatial data includes topological relations among geospatial objects, which can be displayed by the 9-intersection model (Egenhofer, 1994). Semantic of geospatial data also includes qualitative proximity relations referring to distance among geospatial objects. Reality described by geospatial phenomena constantly evolves in time. In order to capture this evolution, until now, succession of states of the reality in time was usually represented in GIS by snapshots of this reality (Peuquet, 2001). For example, temporal changes in a city were described as a collection of maps representing the same city at different times. Thus, the underlying temporal representation was a discrete one, and the main entity to be represented was the geospatial object. This discrete representation of different states of the reality (the set of geospatial objects) makes it difficult to represent changes between the snapshots. Thus, the contemporary research focuses on more realistic representation of changes that could allow dynamic analysis of spatial data. So one of the issues is how to develop appropriate spatiotemporal data models that could be able to represent those changes (Tryfona and Jensen 1999). A key idea is to understand that entities that compose reality differ according to their temporal mode of existence (Grenon and Smith, 2004). In the first temporal mode of existence, entities have a continuous existence. These entities preserve their identity over time even though they encounter various changes. Examples of these entities are geographic object such as countries, mountains, buildings, etc. In the second temporal mode of existence, entities are occurrents and they unfold trough a period of time. Such entities represent changes and are more often termed as processes or events: passage of a storm, crossing of a border, destruction of a building, etc. This vision of the reality results in extended kinds of ontologies including events. Object-Event models such as GEM, Geospatial Event Model proposed by Worboys and Hornsby (2004) are based on this underlying ontological theory where entities of the world may be seen either as object or as events. The Geospatial Event Model extends the traditional object-based geospatial models by representing classes of geo-objects and geo-events, each of which may have attributes, relations to other geo-objects or geo-events. For example, the *plane_take_off* event may have attribute *depart_time* and the relation *take_place_on* with the object *runaway*. Now modeling events also brings the question of what type of relation may involve events and objects. In the Geospatial Event Model, based on the terminology of Grenon and Smith, the following classes of relations for events and objects are described: *creation*, *sustaining in being*, *reinforcement/degradation*, *destruction*, and *splitting/merging*, so each of these classes may include different verbs describing possible relations. Finally, just as geospatial objects, events have thematic, spatial and temporal features. Events are related to a spatiotemporal setting: they may be described on a point, a line or a region of space, they may be instantaneous or they may extend on a finite interval of time. All these possibilities need to be represented in the ontology of a dynamic domain.

Objects-Event models provide a foundation for modeling dynamic geospatial domains and enable to fulfill tasks such as event detection. The utility of event-based models as already been proven in domain such as representation of events in dynamic video scenes (Kojima et al. 2002; Olivier et al. 2004; Xin and Tan 2005). Semantic analysis of events in dynamic scenes, which aim at helping in visual surveillance, has essential task to detect and track moving objects, label and classify them, ascertain and represent special relationships among them or with the environment, and finally analyze and express behaviors or events in this dynamic scene (Shah 2002).

3 An integrated Approach for Reasoning on Geospatial Object and Events

In this article, we will propose an approach for reasoning on geospatial objects and events, in order to facilitate semantic mapping between ontologies that represents geospatial object and event concepts. Reasoning on relations between geospatial object and event concepts of different ontologies can help to discover knowledge that is relevant for disaster management. The first goal of our approach is to describe by mean of examples what are the heterogeneities that may arise between ontologies of geospatial object and event concepts, which are obstacles to integration of these ontologies. The second goal is to propose an hybrid model, that is, a quantitative and qualitative similarity model, that will help to achieve mapping of concepts between these ontologies. The hybrid model and the resolution rules we will define can be used to reason on relation between object and event concepts of two ontologies.

3.1 Representation of object and event concepts

In a dynamic reality such as in natural disaster, representation of events is important, as the data sources that capture this reality such as in data captured by a video surveillance, contains objects and events at the same time. However, as geospatial objects, events may have multiple and heterogeneous representations. For example, it is well-known that geospatial objects may be represented at different levels of spatial granularity, thus giving the problem of multi-representation. The same fact may arise for events, which may be seen in different scales depending on applications. Moreover, events and objects may represent a same reality, and just as there are different methods to cope with the problem of reconciliating ontologies that represents similar geospatial objects, we need methods to help in the reconciliation of ontologies that represent geospatial objects together with geospatial events. In this section, we will describe how geospatial objects and events can be represented in our approach and we will provide a working example. Latter in the next section we will present some of the heterogeneity conflict we have identified that can affect ontologies describing objects and events.

Concepts are mental devices used to understand and communicate different ideas that help to structure the domain of discourse (Gahegan and Pike, 2006). In our approaches, concepts can be geospatial objects or geospatial events. Any concept has an associate spatiality, temporality and set of thematic features. Spatiality of a concept denotes its position in space, according to a reference, and its geometry. Types of geometries may be point, lines, polygons and volumes. Temporality of concepts is the duration of concepts in reality. Geospatial objects have a duration that can be described by a valid time interval $[t_s, t_e]$, where t_s is the time of appearance of the object in reality, and t_e is the time when the object disappears from the reality. However, geospatial event does not necessarily have a temporality that can be described by an interval, since some events may be considered as instantaneous. Consequently, types of temporality for an event can be a time point, t_{event}, describing an instantaneous event, or a time interval $[t_s, t_e]$, describing a spanning event. For example, the event *vehicle crossing a country border* may be considered as instantaneous, while the event *construction of a bridge* may have a duration of one year. Finally, semantic of concepts (objects or events) is described by their thematic features, such as color, function, material, etc. In order to facilitate discussion we adopt the representation of concept given in figure 1. In this figure, OT, OS, OR and OF refer respectively to object temporality, object spatiality, object relations and object features. ET, ES, ER and EF refer respectively to event temporality, event spatiality, event relations and event features.

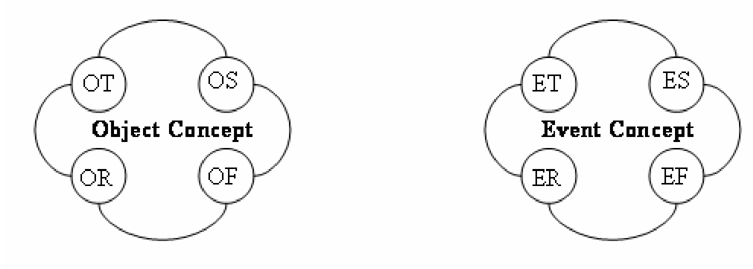

Fig.1. Geospatial Object and Event Representation

In addition, in an ontology each concept has relations with other concepts of the ontology, so the ontology can be represented as a graph with labelled nodes, which are concepts, and labelled arcs, which are relations between concepts. Relations between concepts depend on the type of concepts they involve. We distinguished four categories of relations, that is: relations between geospatial objects (OO_Rel), relations from a geospatial object to a geospatial event (OE_Rel), relations from a geospatial event to a geospatial object (EO_Rel) and relation between events (EE_Rel). These categories of relations are shown in figure 2.

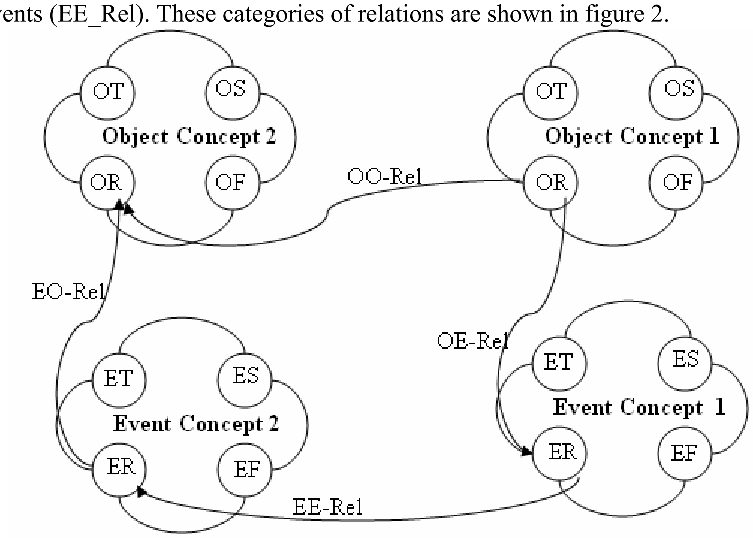

Fig.2. Categories of Geospatial Object and Event Relations in object-event ontology

In the following, we will show an example in order to present problems encountered in disaster management when having to deal with ontologies representing object and event concepts. Suppose on one hand we have an ontology of a city that represent the risk of fire for different places and buildings. Each instance of concept (places and buildings) of this ontology have different attributes that are relevant to assess risk of fire, for example, the number of floors, the last time the building was inspected by the fire department, etc. This ontology is evolving because of the apparition of new types of buildings, new attributes that are relevant to assess risk of fire are considered (for example the attribute emergency exit), some buildings are destroyed (for example Building B), some new roads are been constructed, etc. On the other hand, consider an ontology that have represented and classified all kinds of incidents (events) that may be related to fire incidents, with their causes, the place and time where they happen, the severity of damage, etc. On figure 3 and 4 we present a small part of the city that we will take as our working example. In this example, we also suppose that for prevention of fires, analysts in disaster management want to evaluate if the risk of fire associated to different geospatial objects such as forest cover and buildings was correctly assessed. So they need to perform a comparative analysis between geospatial objects, their attributes, and the incidents that really happened. For example, they may ask the question: does frequent inspections of buildings are related to reduced fire incidents?

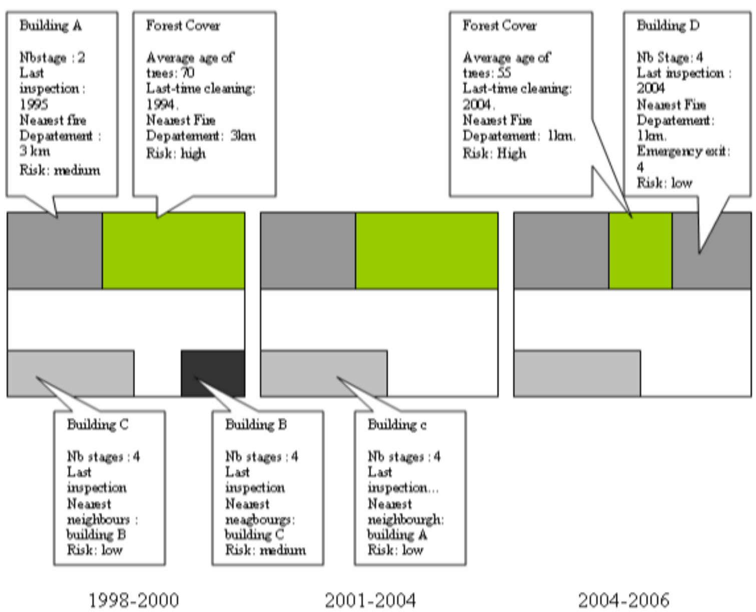

Fig.3. Working example: snapshots of reality city at different times

The problem in this scene is that ontology representing the city and the ontology representing the fire incidents use different representations of time (snapshots and events) so answering the question requires to relate both ontologies. In the following section, using this working example, we will define some heterogeneities that are obstacle for the semantic reconciliation of these ontologies.

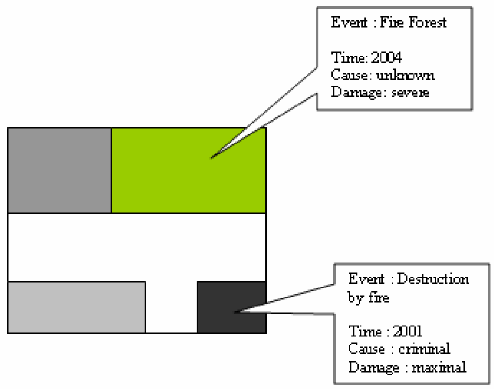

Fig.4. Working Example: events related to fire incidents for the same reality

3.2 Heterogeneity conflicts in evolving geospatial objects and events ontologies

We have seen that an event may be defined as an obvious change of important features which we are interested in (Howarth and Buxton 2000). This suggests that an event may be represented with a different manner in different ontologies. In this section we will describe some of the heterogeneity conflicts that may arise when comparing ontologies which contain geospatial object and event concepts. The first conflict we describe is the conflict we called heterogeneity of temporal paradigm. This heterogeneity results from the different temporal point of view that can be taken to describe a changing reality. On one side, entities of the real world may be abstracted as object concept, for example the concept *speed*. On the other side, the same reality depicted by the concept *speed* may be described by the event concept *displacement of an object*. In our framework, we will call this kind of divergence between these ways of describing temporality as *heterogeneity of temporal paradigm*. This heterogeneity is specific to ontologies containing events since in ontologies where concepts are not distinguished between categories of object concepts and event concepts we don't have to make this choice between the possible representations.

Conflicts caused by heterogeneity of temporal paradigms
These conflicts arise when a same concept is represented using different temporal paradigms in distinct ontologies:

1. A concept is represented as a geospatial object concept.

2. The same concept is represented as a geospatial event concept.
3. The concept is represented as a set of geospatial object concepts succeeding in time.

An example of this heterogeneity is that the destruction of the building B is represented by a succession of scenes of 1998-2000 to 2000-2004 in the ontology of geospatial objects and it is represented by the event: destruction by fire of building B in the incident ontology. So this example show that an event can be represented explicitely by a geospatial event concept, or that it can be represented implicitely by a serie of states for the same object at different times.

Conflicts caused by temporal heterogeneity.
Another type of conflict is the conflict caused by temporal heterogeneity. Temporal heterogeneity we define here arises when a same event is represented by different temporal types, i.e. by a time interval and a time point in different ontologies. For example, in airport ontology, the event of plane take-off may be considered as an instantaneous event (by referring to the moment to plane gets off the runway) or as a spanning event (if length of time between the moment starts to roll and the moment where it takes off is important to consider). In our fire incident example, temporal heterogeneity between events may be that a same event *destruction by fire* is described by a temporal point (2001) or more precisely by a time interval [from 2001/12/20 13:40; to 2001/12/20 23:12].

Conflicts caused by spatial heterogeneity
Spatial heterogeneity between multiple representations of geospatial objects is already a recognized problem, and an obvious example is that at different scales a city may be seen as a point on a country map or as a polygon on a regional map. In the same way, events may be seen spatially at different scales, for example in meteorology the passage of a depression may be seen as lines (pressure iso) or as a region affected by this depression. In our fire incident example, spatial heterogeneity between events may be that the event *destruction by fire* can be associated to a building or, in an ontology requiring more precision in the representation of this event, to only a certain part of the building that was affected.

Conflicts caused by semantic heterogeneity
Conflicts of semantic heterogeneity affect both object concepts and event concepts. They include different names for the same concept (object or event), or different definitions to describe the same concept. Different thematic features may be used to describe a same concept, for example, the event *destruction by fire* can have attributes *time of event*, *cause*, and *degree of damage*, while in another ontology the same event destruction by fire can have attributes *time of event*, *nearest fire department*, *intensity of fire*. A concept can have different relations with surrounding concepts in different ontologies. This includes concepts having relations with different concepts or concepts having relation with the same concept but where the nature of the relation is different.

In order to cope with the different conflicts identified in this section, we propose in the next section a hybrid model for similarity mapping that will help to relate object and events of different ontologies.

4 A Hybrid Similarity Mapping Model for relating object and events concepts

The conflicts due to heterogeneities described in the previous section need to be addressed in order to make it possible to share knowledge different ontologies ontology. One way of achieving this task is to identify the relation between concepts of distinct ontologies with a model of similarity. It can be seen that a model being designed to relate concepts of ontologies describing geospatial object concepts and geospatial event concepts must consider the following cases:

1. an object concept of a first ontology can be related to an object concept of a second ontology
2. an object concept of a first ontology can be related to an event concept of a second ontology
3. an event concept of a first ontology can be related to an object concept of a second ontology
4. an event concept of a first ontology can be related to an event concept of a second ontology.

To obtain relevant information in order to map geospatial object or event concepts, we argue that both qualitative and quantitative aspects of similarity between concepts have to be considered. Qualitative aspect gives information about the nature of the relation between concepts, for example if the concept is more general than the other one or if they are only overlapping. Quantitative aspect gives information about the degree of similarity between the concepts. Both approaches are necessary in order to identify the most coherent relation between concepts with respect to reality and with respect to the user need. Consequently, in our approach we will propose to use a model that gives qualitative and quantitative output. We also consider that a complete model should consider all the aspects of definition of concepts, that is, semantic similarity through thematic features, spatial features and temporal features and finally relations between concepts. In the following, we will first give definition for our framework and define what constitute the hybrid model of similarity mapping, then we will show how it can be used with resolution rules and mapping strategies to map between event-object ontologies.

SpatioTemporal Object-Event Ontology

A spatiotemporal object-event ontology is O^i is defined by $O^i=(C, R)$ where $C=\{c_i, i=1,2,\ldots\}$ is the set of spatiotemporal concepts of the ontology, and R is the set of relations $r=(c_i, c_j, type\_rel)$ between concepts of the ontology.

Concepts of SpatioTemporal Object-Event Ontology
Set of concepts of the SpatioTemporal Object-Event Ontology can be of two categories: Object concepts and Event concepts, in order to represent classes of geospatial objects and geospatial events of the real world. Object concepts are labelled OC and Event concepts are labelled EC. Each concept *c* is defined by a set of properties which are further refined in the following categories: thematic properties F, temporal properties T, spatial properties S and set of relations R with other concepts of the ontology (figure 5 and 6).

Relations between concepts of SpatioTemporal Object-Event Ontology Relations between concepts may be of four different categories, depending on categories of concepts being involved: relations from object concept to object concept (OO_Rel), relations from object concept to event concept (OE_Rel) (figure 5), relations from event concept to object concept (EO_Rel), relations from event concept to event concept (EE_Rel) (figure 6). Those relations proposed in our framework are general and in further works they could be further refined in more specific relation. However, as we would consider more specific relations between event and object concepts, reasoning on these relations would be hard unless we introduce an ontology of event that could classify these relation in order to allow inferencing between them.

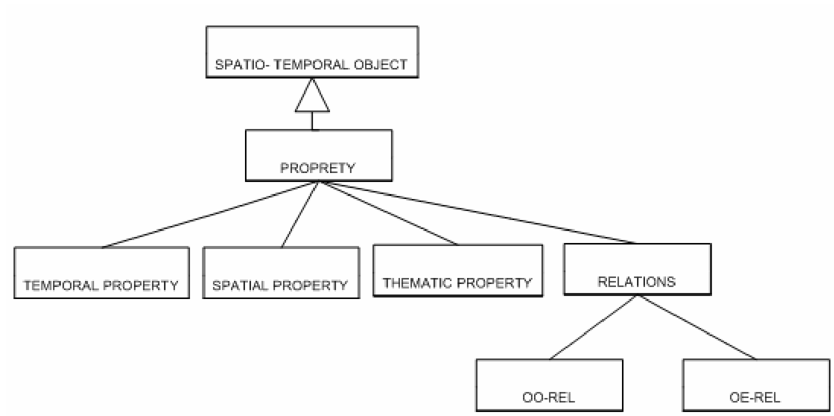

Fig.5. Description of object concepts of SpatioTemporal Object-Event Ontology

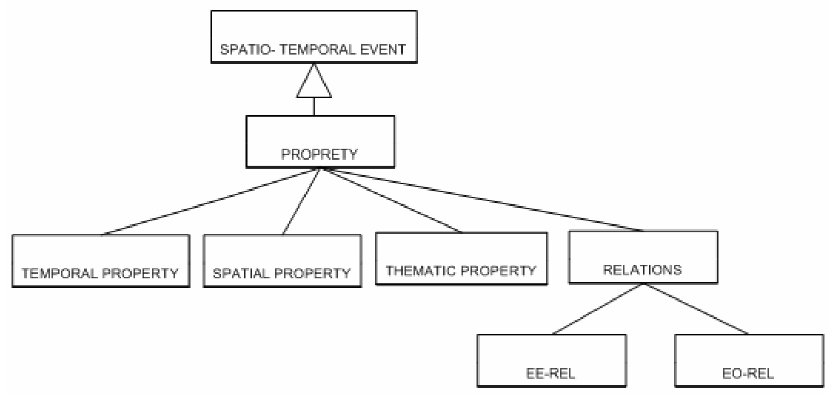

Fig.6. Description of event concepts of SpatioTemporal Object-Event Ontology

Semantic Similarity between concepts of SpatioTemporal Object-Event Ontologies

Semantic similarity between concepts of the ontologies depends on the type of concept being compared, either object concepts or event concept, since object concepts don't share the same relation with object concepts than with event concept, and reciprocally. For the development of our semantic similarity model between object concepts and event concepts, we inspired from the representation of concepts proposed in the geosemantic proximity model (Brodeur 2004), which described concept as set of intrinsic and extrinsic properties, and adapted it to describe similarity between event concepts. This leads us to identifying new relations that can be established between event concepts, or object and event concepts. In the model we propose in this article, semantic similarity is function of similarity between thematic properties and relationships properties of concepts that are compared. By considering that thematic properties of a concept are analogous to internal part of concept and relationship properties are analogous to boundary between the concepts and the surrounding concepts of ontology, semantic relation can be analogous to topological relation between regions as described by Egenhofer (1994). The set of thematic properties is labelled OF for object concept and EF for event concept, while the set of relationship properties is labelled OR for object concept and ER for event concept. The subscript i for example in OF_i indicate set of thematic properties for object concept c_i.

Event-to-Event semantic similarity

The model of semantic similarity between two event concepts E1 and E2 is a matrix which compares their EF and ER sets of properties:

$$S(E1,E2)=\begin{pmatrix} EF_1 \cap EF_2 & EF_1 \cap ER_2 \\ ER_1 \cap EF_2 & ER_1 \cap ER_2 \end{pmatrix} \quad (1)$$

Semantic similarity between events is a qualitative relation that depends on the state of this matrix, that is on whether the four intersection sets it contains are empty or not. We denote by $\varnothing$ an empty intersection, by $\neg\varnothing$ a non-empty intersection and by $\equiv$ an intersection that is equivalent to union of the set of properties. An empty intersection $\varnothing$ express that there is no common properties between the compared sets and a non empty intersection $\neg\varnothing$ express that there is at least one common property between the compared sets. An intersection that is equivalent to union $\equiv$ indicates that all properties of set being compared are common, in other word, sets are equals. Thus, we identified that semantic similarity between events can verify one of the relations on figure 6.

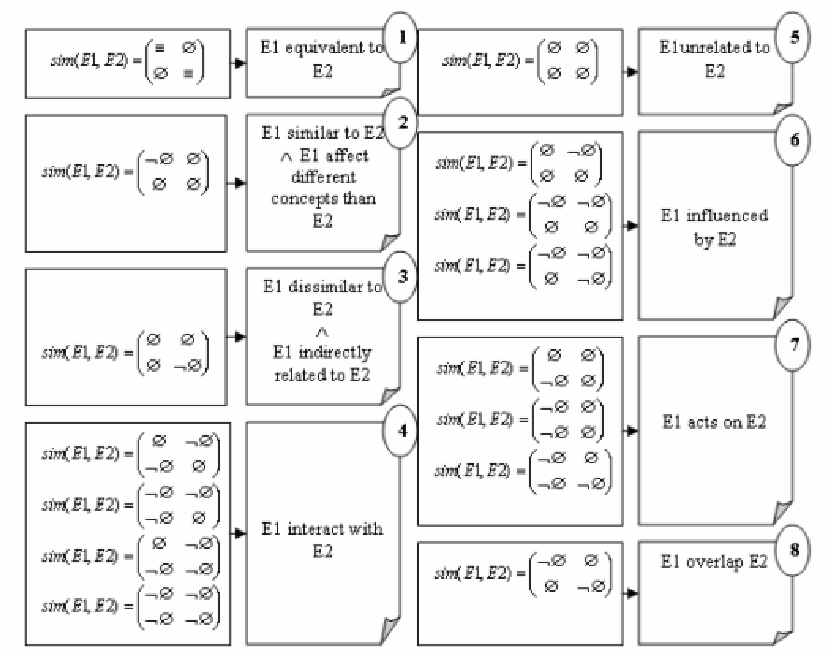

Fig.6. Relations of semantic similarity between two events E1 and E2

The semantic similarity relations expressed on figure 6 allow relating events from different ontologies. In the case 1, E1 and E2 have the same sets of thematic and relationship properties so they are equivalent. In the second case, E1 and E2 share some thematic properties but they affect different objects and they may be related to different events. The anti-symmetrical case is the third one where event have no thematic properties in common but they share relationship so they may affect the same objects concepts or be related to similar events. Consequently in the third case both events E1 and E2 may be indirectly related by mean of a third concept. In the case 5, E1 and E2 share no thematic properties and no relationship so they are not related. In the case 6, thematic properties of E1 are common with relationship of E2, meaning that E1 is partly determined by one ore more relationship of E2. Consequently, E1 is influenced by E2. For example, suppose we compare the event concepts *forest fire* and *lightening* from two different ontologies. The event concept *forest fire* has thematic property *cause: thunder storm*. and the event concept *lightening* has relationship *lightening part-of thunder storm*, so thematic property of *forest fire* is common to relationship of *lightening*. This cause *forest fire* to be influenced by *lightening*. The case 7 is the opposite of case 6 where relationships of event E1 are common with thematic properties of event E2, then E1 acts on E2. Case 4 combines cases where E1 is influenced by E2 and E1 acts on E2, so we define this relation as E1 interact with E2. Finally, in the case 8, we give the relation where event concepts E1 and E2 may overlap because they share some thematic and relationship properties to a certain degree.

Event-to-Object semantic similarity

The model of semantic similarity between event concept E1 and object concept O1 is a matrix which compares their EF, OF, ER and OR sets of properties:

$$S(E1,O1)=\begin{pmatrix} EF_1 \cap OF_1 & EF_1 \cap OR_1 \\ ER_1 \cap OF_1 & ER_1 \cap OR_1 \end{pmatrix} \tag{2}$$

$$S(O1,E1)=\begin{pmatrix} EF_1 \cap OF_1 & EF_1 \cap OR_1 \\ ER_1 \cap OF_1 & ER_1 \cap OR_1 \end{pmatrix} \tag{3}$$

In the same way as for semantic similarity between event concepts, semantic similarity between event concept and object concept depends on the state of this matrix, and gives relations shown on figure 6 (replacing E2 with O1), since object and event concepts may also be related by relations Acts on, Influenced by, Interact with and may overlap if an object concept is represented by an event concept in the other ontology, or inversely.

Object-to-Object semantic similarity

The model of semantic similarity between event concept O1 and object concept O1 is a matrix which compares their OF and OR sets of properties; this matrix verifies one of the cases presented in figure 6:

$$S(O1, O2) = \begin{pmatrix} OF_1 \cap OF_2 & OF_1 \cap OR_2 \\ OR_1 \cap OF_2 & OR_1 \cap OR_{21} \end{pmatrix} \tag{4}$$

Now we proposed that the overlap sets contained in the matrix of equations (1), to (4) can be evaluated quantitatively in order to give the degree of semantic similarity between concepts being compared. Quantitative degree of similarity is required in order to determine if the semantic similarity relation that has being identified by semantic similarity matrix from equation (1) to (4) are significant. For example, if degree of overlap between properties is very low, it would be wrong to consider that two concepts, for example, interact with each other.

Degree of overlap, denoted by D=D(c_1, c_2), compared the number of common (thematic or relationship) properties to the number of (thematic or relationship properties) of the first concept c_1; it always gives a value between 0 for disjointness and 1 for equivalence relations, and is of the general form:

$$D(f, semantic, c_1, c_2) = \frac{f(c_1) \cap f(c_2)}{f(c_1)} \tag{5}$$

where *f* is a set of (thematic or relationship) properties. Degree of overlap is computed for each intersection set of the matrix (four intersection sets), and to obtain a global semantic similarity D(semantic, c_1, c_2) which range between 0 and 1, we compute the normalized sum of these four overlaps. Semantic similarity value is also asymmetrical since qualitative relations are asymmetrical. Now we also consider degree of similarity between temporal and spatial properties by considering the overlap of temporal attributes and spatial attributes of concepts, D(temporal, c_1, c_2) and D(spatial, c_1, c_2) these degree of overlap can be computed by adapting the general form of overlap given by eq. (5). In order to give a global value of similarity, that is global similarity between two concepts, we define a three dimensional similarity space composed of the semantic similarity, temporal similarity and spatial similarity axis. In this similarity space we can define the vector of similarity $V(c_1, c_2)$:

$$V(c_1, c_2) = \big(D(semantic) \quad D(temporal) \quad D(spatial)\big) \tag{6}$$

Global similarity between concepts is given by the length of this vector in the similarity space:

$$Global\_Sim(c_1, c_2) = \sqrt{\sum_{i=1}^{4} \big(D(f_i, c_1, c_2)\big)^2} \tag{7}$$

Results of assessing similarity in a qualitative and quantitative way are the first steps toward mapping the object-event ontologies. For reasoning on the obtained results, we need to define a way to analyse this result in order to decide if two concept are to be mapped or not and which relation is going to hold between them. For this purpose we propose to define some example of conflict resolution rules to resolve some of the conflicts given in section 3.2 and example of mapping strategies to handle the mapping process. Resolution rules are logics to follow for a given state of the relation between concepts. These resolution rules and strategies are shown on table 1.

Table 1: Resolution rules and mapping strategy

Identified relation	Conflict to resolve	Resolution Rules	Mapping strategy
global_sim (O1, E1)=1	Temporal paradigm heterogeneity : object and event may refer to same reality	O1 and E1 are same entity	Establish a synonymy relation between O1 and E1
global sim (O1, E1) between 0 and 1 exclusively	Temporal paradigm heterogeneity: object and event may refer to a similar reality but O1 and E1 shows either semantic,spatial and/or temporal heterogeneity	1) If O1 and E1 are semantically unrelated O1 cannot be similar to event E1 even if they share spatial or temporal 2) If O1 and E1 are semantically related , but temporally or spatially disjoint, O1 cannot be equal to E1 because they don't overlap in space and time	1)Establish no direct relation between O1 and E1 2) Establish no direct relation between O1 and E1 3)Establish semantic, temporal and spatial relation between O1 and E1

		3) If O1 and E1 are semantically related , and temporally and spatially non disjoint, O1 can be related to E1	
sim(O1, E1)=0	O1 and E1 represent different reality	O1 and E1 are not related	Establish no direct relation between O1 and E1
sim(O1, O2)=1 $\wedge$ r=(O2, E2, OE_Rel)	Finding matching objects in both ontologies to find object-event relation	Since O1 and O2 are equivalent, relation r between (O2, E2) also hold for between O1 and E2	Establish relation r between O1 and E2
sim(O1, O2) between 0 and 1 exclusively and there is relation r between (O2, E2)	Finding matching objects in both ontologies to find object-event relation	Since O1 and O2 are related, relation r between (O2, E2) can help to find relation between O1 and E2. For example if O1 and O2 are related by O1 is specialisation of O2 and O2 participate to event E2, we can deduce O1 participate to E1.	Deduce relation between (O1, E1) from relation between O2 and E1.
sim(O1, O1)=0	O1 and O1 represent different reality	O1 and O2 are not related	Establish no direct relation between O1 and O2

With these resolution rules and mapping strategies, we underline some general rules that can be used to map event and object concepts of ontologies. We underline the fact that relation existing between geospatial objects and geospatial events in the same ontology must be used to discover relation between objects of the first ontology and events of the second ontology. In application such as disaster management, this can help to discover if some geospatial objects were implied in an event represented in another ontology. In our working example, we could find with the model of mapping and resolution rules which buildings and place were implied in fire incident and thus analysing attributes that were not necessarily represented in the fire incident ontology. The rule we have underline are general but we can fix explicitly a whole set of resolution rules in a given domain with a known set or possible relations from objects to events in order to automate as much as possible the mapping process. Results may be even more concluding using a knowledge base to reason on different categories of relations.

5 Conclusion and Future Works

In this paper, we discussed the problems of heterogeneity that can be encountered when we want to share knowledge between ontologies representing geospatial objects and geospatial events in disaster management applications. We have proposed an hybrid similarity model that considers both qualitative and quantitative approaches for the similarity measurements between object and event concepts in different ontologies, and that can help to resolve some of the described heterogeneities, and help in discovering new relations between event and object concepts. Based on the results of this model, we have proposed some resolutions rules and mapping strategies to help in discovering relations between objects and events. This helps us to better analyse a dynamic phenomena such as in natural disaster management. This work is a part of ongoing PhD project and research will be conducted to improve the proposed approach by considering types of relations between objects and events in a real world case. In future works, we attempt to extend this work to help in achieving semantic interoperability in a dynamic network of data sources. This will help to a more effective decision making in disaster management by providing solutions for sharing relevant geospatial data between multiples data sources.

Acknowledgment

This research was made possible by an operating grant from Natural Sciences and Engineering Research Council of Canada (NSERC).

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