Semantic Trajectory Modeling for Dynamic Built Environments

Christophe Cruz
Le2i, CNRS FRE 2005, Arts et Métiers,
Univ. Bourgogne Franche-Comté,
Bâtiment I3M rue Sully, Dijon, France
christophe.cruz@ubfc.fr

***Abstract*—This paper presents a data model to capture moving and changing objects in the context of dynamic built environment. Building elements are subject to change which represents semantic trajectories crossing trajectories of users. These semantic trajectories in dynamics built environment permit to capture fine-grained activities and behaviors of users and objects. The data model is based on ontology and description logics to capture logic constraints on semantic trajectories.**

Keywords—semantic trajectories; description logics; ontology; built environment

I. Introduction

Rapid advances in technology are reshaping our economy and society notably in the domain of Smart Cities [1] and Smart Buildings [2]. Designing smart environments [4] requires a variety of disciplines including artificial intelligence, pervasive and mobile computing, robotics, middleware and agent-based software, knowledge modeling, sensor networks, big data and cloud computing. A smart environment can be defined as an environment *able to acquire and apply knowledge about the environment and its inhabitants in order to improve their experience in that environment* [12].

When considering BIM (Building Information Modeling) as integrating digital technology for delivering high-efficiency built life-cycle management solutions, a BIM system [05] is a central system that allows to manage various types of information, such as the planning of enterprise resources, resource analysis packages, technical reports, meeting reports, etc. However, the main feature of a BIM system is the 2D/3D modeling with data management, data sharing and data exchange during the lifecycle of the building. Thus, a smart environment should be built upon BIM to integrate data and services. The combination of BIM and smart environment drives systems to be user-centric in the domain of Smart Buildings and Smart Cities.

User centric systems provide advanced services to users based on information at the right place, at the right time. Consequently, user activities and behaviors are considered as important features to understand the needs allowing the system to provide a high level of service quality. The questions are how to capture the activities and behaviors of users? And how to consider these activities and behaviors? [3] Before answering the second question which is out of the scope of this paper, we should focus on the first question. What are the relevant data structures able to capture the activities of users and objects in a built environment? Actually, objects used by users are part of its activities and behaviors during interactions.

As a first step to answer this question, indoor/outdoor positioning devices offer the ability to determine the trajectories of users and objects. The spatial trajectory idea originates in the movement capture of moving objects in a geographical space over some period of time [6]. Raw data are data captured from devices. These raw data requires pre-processing to undertake further processing such as indexing and retrieval processing, trajectory analysis, trajectory pattern mining or activity recognition based on trajectories. Available works and algorithms provide efficient mobile data management and mining techniques, but they focus on raw trajectories [13][14]. In addition, they are able to produce knowledge about users such as trajectory classifications, but what do they tell us about the fine-grained user interactions with its changing and moving environment?

User contextual information is usually missing. This information contributes to creating significant semantic knowledge about users' behaviors and activities. Semantic is contained in the geometric properties of the spatio-temporal stream such as stay points. But semantics is also contained in the geographic space (e.g. a shopping mall or a hospital) on which entities (i.e. users and objects) move and change. Therefore, semantic trajectories appear as a growing trend that emerged in spatio-temporal knowledge discovery. It aims at providing an understanding with regards to the motion of users and objects considering its environment [7].

However, a built environment is dynamic. The concept of dynamic built environment comprises both natural and artificial assets constructed by humans such as cities, infrastructure, or public spaces. The essence of a dynamic environment can be defined through its opposite definition namely static environment. An environment is considered as static when the objects are stationary without moving or changing. An environment is considered as dynamic when the objects are capable of movements and may even change its shape, size, change its attributes (e.g. the entry gate is closed) or its semantics (e.g. the room 237 is now a meeting room).

To understand one of the most salient questions, challenges, and insights that emerged from the semantic trajectories, any user or object including building object (e.g. an entity) has all its property able to change over time. That means its localization, its size, its properties (open/close for a door) and its relationships with the environment (two walls are connected) event its semantics is mandatory to change. Consequently, this primer aims at providing a data model for Semantic Trajectories in Dynamic Environments named STriDE. This model receives tracking results of changing entities by combining raw data pre-processing and semantic definition of the environment (e.g. BIM). This paper proposes an ontology-based model to index STriDEs, its components and the interrelationships Description Logics and logic constraints. Based on the *Continuum* model [15][16][17][18], the proposed model combines 2D/3D semantic environments and semantic trajectories, an indexing model for time-dependent large-scale graph with semantic resources. The *Continuum* model was defined to capture moving and changing objects. The STriDE derived from the *Continuum* model does the same but can capture at the same time moving and changing entities of the environment.

The paper is organized as follows. First, a description of different models is presented. Second, some elements are given about the *Continuum* Model. Third, the STriDE model is provided. Last second concludes the paper.

II. BACKGOUND

Spatio-temporal modeling is a very heterogeneous domain whose user needs, data formats and structures are relatively varied. Therefore, identifying generic characteristics for modeling an entity over time establishes itself as the preliminary work in the design of any spatio-temporal model. The life cycle of an entity over time can be summed up in a succession of states and transitions. States are intrinsic changes in the entity while transitions are modeling more external factors that have led to the passage of the entity from one state to another state. Several models in the literature were defined around these two major parameters specific to spatio-temporal evolution. Relational databases have emerged as the preferred support of the spatio-temporal modeling, but new requirements for the design of future GIS highlight the lack of high-level semantic and qualitative analytical capabilities for the study of spatio-temporal dynamics. A spatio-temporal entity is a representation of the real-world entities composed of an identity, descriptive properties, and spatial properties. While the identity describes a fixed component of the entity, alphanumeric and spatial properties can vary over time and are its dynamic part. When the identity of an entity varies, there is a particular kind of evolution where the spatio-temporal entity is transformed into a new entity. In the literature, there are two main types of spatio-temporal entities: 1) moving objects, and 2) changing objects [23]. In this work, the focus is made on the object which can move and change at the same time or over time.

This section consists of four subsections. First, an introduction to spatio-temporal models for changing entities is given. Then, the trajectory modeling of moving entities is introduced. Next subsection deals with ontology-based models, and the last subsection presents the identity representation of entities over time.

A. Spatiotemporal Models for Changing Entities

The evolution of a spatial entity over time can be seen either as a succession of states (or representations) of the entity, or as a succession of transitions that involved this entity over time. Some models for spatial dynamics are based on discrete approaches such as: the snapshot model [26], the Space-Time Composites model (STC) [27] and the Spatio-temporal Object model [28]. They represent only sudden changes which make difficult to identify processes such as movements of an entity in a geographical environment. Other models focus on the identity of the spatial features and how it evolves along time [29]. Another kind of models use the intersection matrix to identify changes in topological relations between evolving features [30].

Another type of models is the so-called event and process-based approach. This approach considers that spatial entities operate under the impetus of an event or a process, the aim of this approach is to analyze the causes and consequences. An example of this type of model is the Event-Based Spatiotemporal Data Model (ESTDM) [31]. The ESTDM model describes a phenomenon through a list of events; a new event is created at the end of the list whenever a change is detected. However, this model considers only raster data and the causal links between events are hardly highlighted in this model. An alternative to ESTDM is the composite processes [32]. The composite process model deals with some of the limitations of the ESTDM. It is designed to represent the links between events and their consequences. Moreover, the authors argue that the data model must di□erentiate what is spatial, temporal, and thematic. Another example is the model of topological change based on events [33]. This model represents change of a geographic environment as a set of trees. Each tree is connected to the next and the previous through its nodes. The link between two trees is a topological change that reveals the creation of an entity on the geographical environment, the deletion of an entity, division or merger of entities, or no change. The succession of these topological changes enables the representation of complex changes.

A natural way to model dynamic phenomena is through a graph. Entities and their states are vertex and the relations as edges. Previous research has employed this approach. For instance, [34] used it to model urban spaces. While in [35], a similar approach was used to study road networks. Another example is [36], in which the authors use graphs to model the structure of a territory. However, all these examples focus on the spatial structure and omit the temporal dimension, which requires additional modeling procedures.

B. Spate-Temporal Models for Moving Entities

Currently new datasets containing large amounts of tracking data are becoming available. These datasets contain the recorded position of a traveling entity while it moves into space. In order to extract knowledge from this information a new set of tools and algorithms are being developed in the research world. In [6], the authors present a survey on current approaches and techniques for the definition of *semantic trajectories* within the field of *data mining*.

A raw *trajectory* comprises the record of the position of a moving entity, during a time interval, in which this entity moves for some meaningful purpose. In some domains, the identification of the beginning and the end of the trajectory is evident, while in others it might requires some domain specific criteria. The positions and intervals allow us to identify possible *stops* along the trajectory. Additional information can be obtained by linking the trajectory to external data sources. For instance, comparing the tracking records of a person with a set of places could tell us what places the person has visited [6]. By analyzing trajectories, it is possible to identify stops and elements on the route. Then, *annotations* can be added creating a *semantic trajectory*. An analysis of the trajectory can also lead to the identification of behaviors of moving entities. For instance, by analyzing the elements on the route of a tracked person it could distinguish a tourist from a delivery service [37]. The authors implement their approach with a relational DBMS, using as a case study data from the migrations of white storks.

C. Ontology-Based Models

Modeling of a phenomenon generates a complex graph of relationships, such as temporal, spatial, and semantic relations. The idea of taking advantage of ontology-based approach is not new to model trajectories. In [10], the approach integrates domain ontologies with spatial ontologies to answer queries based on spatial instead of temporal relationships. Ontologies are based on the notions of individuals, classes, attributes, relationships, and events. In an ontology, entities can be managed as individuals and grouped in defined classes. The definition of a class can be further specialized, creating subclasses. Attributes are modeled as properties that represent characteristics, or parameters that entities may possess. Relations are defined as links between entities. Finally, the events correspond to changes in attributes or relationships. The definition of relationships between entities can also be further generalized or specialized. In cases of generalization or specialization for both relation and class definitions, the ontology enables the construction of a hierarchy based on subsuming relationships.

An approach that puts more focus on Description Logics based tools is presented in [38]. Here, the authors propose the use of three different ontologies to address the study of moving entities. The first one is called *Geometric Trajectory Ontology*. This ontology defines the basic concepts for the spatio-temporal definition of the trajectory. Using the elements defined in this ontology, we can specify temporal points, areas, lines, etc. The second one is called *Geography ontology*. In this ontology, the authors describe natural and artificial features of interest for the specific domain. Finally, the third one is called *Application Domain Ontology*. In this ontology, the authors define higher level concepts for specific domains. In [38] the authors test their ideas using data from cars equipped with GPS devices. The data is loaded into a commercial relational DBMS with support for ontological data.

In [39], the authors introduce *SeMiTri* (Semantic Middleware for Trajectories). This software is designed to create *annotations* by analyzing the geometric properties of the trajectory and linking it to background geographic and application-specific data. The proposed system has three parts: 1) *Trajectory computation layer*, here the raw GPS data is cleaned, raw trajectories are identified and each trajectory is divided into trajectory episodes. 2) *Semantic annotation layer*, to link the trajectory to areas it crosses, road networks. It also estimates probabilities of associations between *stops* and geographic features using a Markov model algorithm. 3) *Semantic trajectory analytics layer*, here are the components of the system that compute statistics, and store obtained information. An additional component is the Web Interface, designed to allow the user to define queries and visualize results.

D. Representing the Identity of Entities Over Time

An important concept regarding the evolution of entities is the identity. It can be defined as the uniqueness of an object, regardless of its attributes or values. This feature distinguishes one object from all others. The identity is essential in the conceptualization and modeling of a phenomenon. Its importance while modeling dynamic systems have been identified by previous research such as [40], [24], [25]. However, this concept is very subjective because it depends on the criteria selected by the user to define the identity of an entity. Usually the criteria for the definition of the identity depends on the domain of study (e.g. Fig. 1, ts3 is an urban parcel and ts5 is a dense urban parcel, ts4 is a conifer forest parcel and ts7 is a hardwood forest parcel).

The filiation relationship defines the succession link that exists between different representations of the same object at different instant of time. The filiation relationships reveal their interest in basic changes such as divisions or mergers of entities. Other spatial changes exist to identify the 'parents' and 'children' entities. At this step, filiation is based only on spatial relationships. Therefore, it can be characterized as spatial filiation in the context of spatial changes. In addition, these spatial changes may reveal changes in the nature of the entity. Because of this, the relationship of filiation is intimately linked to the notion of identity. This relationship is essential to maintain the identity of an entity that evolves and to follow its evolution along time. In this process, it is also necessary to identify new entities that can result from evolution.

Previous research has identified two general types of filiation relationships: continuation and derivation [42], [43]. In the first case, the identity remains the same (e.g. fig. 1, ts2 and ts4 is the same parcel). The entity continues to exist, but undergoes a change. While in the second case, a new entity is created from the parent after a certain evolution. Derivation relationships can involve several entities at the same time (e.g. fig. 1, ts4 and ts7 are not the same parcel which is the consequence of the evolution of the parcel nature).

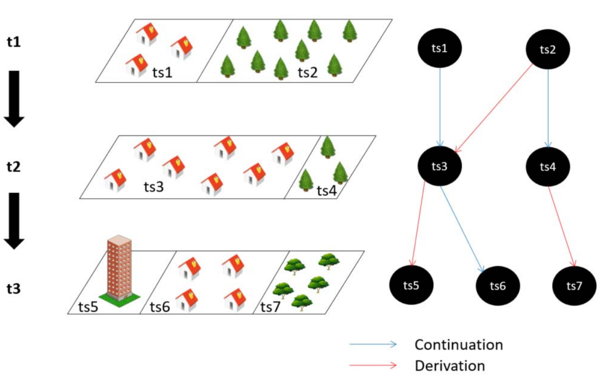

Figure 1. Examples of Continuation and Derivation filiation links for land parcels.

This figure is composed of three-time layers (t1, t2 and t3) and the space is divided into parcels that evolve between two-time layers. The continuation and derivation relationships capture these evolutions during time.

Next section details with the modeling of changing objects and moving object with regards to its identity through continuation and derivation relationship between Timeslices.

III. THE CONTINUUM MODEL

This section is previous work of the author about data modeling of changing and moving entities by going further regarding the state of the art.

A. Representation of changing entities

In [15] and [16], the authors introduced the *Continuum* model, an approach well suited to represent dynamic entities represented spatially as areas. Figure 2 depicts the *Continuum* model as described in [16]. This model follows a *perdurantism* approach. It creates multiple ephemeral representations (*timeslices*) to depict a dynamic entity. Each *timeslice* is valid for a determined time interval. A *timeslice* has four components: 1) An identity, linking it to the object it represents, 2) A set of properties with alphanumeric values, representing different characteristics of the object. 3) A time component that indicates the valid period of time for the *timeslice* and 4) A geometric component, the ephemeral spatial representation of the entity. The model creates a new *timeslice* every time there is a change in the geometry, the identity or in the alphanumeric properties. It is then possible to establish a relationship between a newly created *timeslice* and the one that originated it.

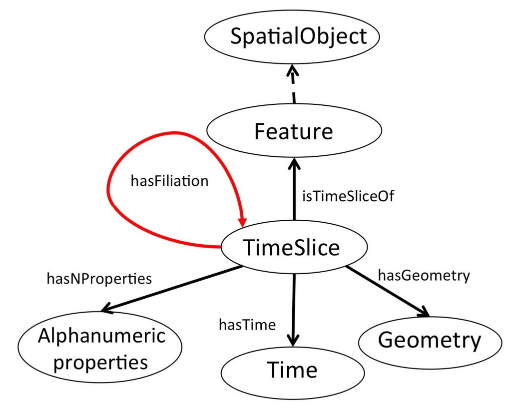

Figure 2. The Continuum model as introduced in [16].

The *Continuum* model takes advantage of GeoSPARQL spatial capabilities as well as methods proposed in ontologies fluent to represent the evolution. In addition, this model allows to represent the filiation relationship between consecutive timeslices associated with an entity. The *Continuum* model was proposed to meet the need of modeling changes that occur on spatial entities. These changes are characterized by spatial changes (related to position or spatial footprints of the entity), related to the semantic or identity-related entities. Therefore, the model integrates and distinguished 5 relations related to space (topological relations), time (Allen Relations [44]), semantics (alphanumeric properties), identity (feature) and filiation (parent-child relationships, 3rd layer fig. 3).

To specify our model, Description Logics [45] is used, then later information is provided regarding how the model has been implemented. This model deals with dynamic entities evolving in time called "timeslice". Each of them can be defined along four components that are identity, spatial, temporal, and semantic as depicted in Figure 2. The identity is the most important component of the model. Each timeslice has an identity defined using a class. Traditionally, dealing with land parcels, a class corresponds to a specific land cover but in the case of timeslice correspond to an individual object, other semantic can be used to underline the uniqueness of a timeslice. Ontologies are useful to organize classes in different semantic levels using a taxonomy. Each class describes a concept and the taxonomy allows to associate the same timeslice to concepts more or less specific. The figure 3 presents how the *hasFiliation* link is specialized into *hasContinution* and *hasDerivation* to consider the evolution of the identity. The 3rd layer specializes the 2nd layer to consider identity and spatial evolution during two-time layers. The 4th layer capture the semantic evolution which is domain dependent which could be Smart Office (e.g. hasNewOpenSpace, hasBiggerRoom, etc.) or Land Registry (e.g. Urbanization, Deforestation, Reforestation, etc.).

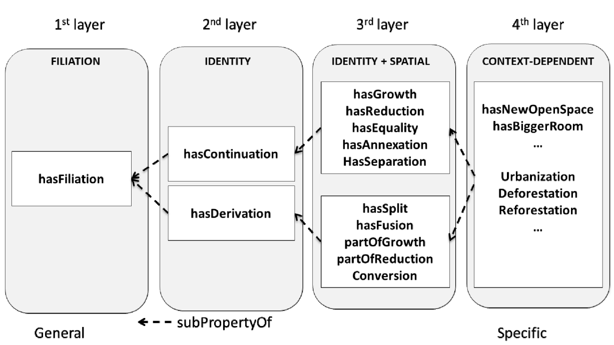

Figure 3. The different layers of the *Continuum* model.

B. *Representation of moving entities*

The *Continuum* model needs to be modified to deal with tracking information of travelling entities. Figure 4 depicts our upgraded version of this continuum model. In the new model, the moving objects are defined as instances of the class Feature. The movements of the objects are spliced into Trajectories, which are semantic units with a defined start and end spatio-temporal points. The Trajectory itself is composed by a set of timeslices, with the same components as in the original version of the continuum model. Following the approach suggested by [38] we developed a Geographic Ontology composed by GeographicFeatures. This ontology allows us to extract new knowledge from the tracking information regarding a static environment.

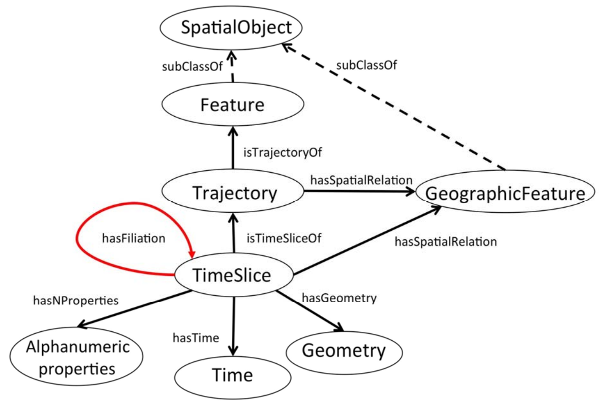

Figure 4. Modified version of the *Continuum* model adapted for moving objects.

The extended *Continuum* data model allows using SPARQL jointly with data stored in a triplestore to compute the following use cases. All the spatio-temporal relationships are precomputed using a preprocessing phase out of the scope of this paper.
The next section describes the STriDE model, the land parcels will not be used anymore, and they will be replaced by building elements. The building elements are represented by 2D plans which have a third dimension or 3D bodies. Previous studies on 3D objects and spatial relationships have been done to represent 3D spatial relationships [46][47][48].

IV. The STriDE Data Model for Dynamic Built Environment

The previous section presented the *Continuum* data model and its extension for trajectories. This section showed how the *Continuum* model can be used to track the movement of people in an environment, but without tracking the evolution of the environment. This section deals with the description logics formalization of the STirDE data model with some modifications of the extended *Continuum* model for trajectories. It mainly consists to link *Continuum* semantic trajectories to building element trajectories using spatio-temporal relationships between instances of TimeSplice objects and integrity constrains regarding time and space.

A. *The Core of Continuum Model Specification*

The Timeslice class is the most general concept and can be specialized in a hierarchy.

$$Timeslice \sqsubseteq T \tag{1}$$

Then, specific concepts are useful for discriminating entities represented while general concepts permit to group entities. Such an arrangement of concepts created a depth index of the hierarchy to evaluate different semantic levels that can be exploited.

$$C_0 \sqsubseteq C_1 \sqsubseteq C_2 \sqsubseteq ... \sqsubseteq C_n \quad (2)$$

where C_0 corresponds to the Timeslice class and n is the depth of the hierarchy.

In order to represent the time in the evolution, we follow the approach suggested by [61] thinking about the temporal domain as a linear structure composed by a set of temporal points (*TemporalPoint*).

$$TemporalPoint \sqsubseteq \top \quad (3)$$

The elements of type *TemporalPoint* follow a strict order, which forces all points between two temporal points t_1 and t_2 to be ordered. By selecting a pair of temporal points $[t_o , t_f]$ we can limit a closed interval of ordered points thus defining time intervals (Interval).

$$\begin{aligned} &Interval \sqsubseteq \top \\ &Interval \equiv \exists hasStartPoint.TemporalPoint \sqcap \\ &\qquad \exists hasEndPoint.TemporalPoint \end{aligned} \quad (4)$$

When a geographic entity or a building element does not change between time points, we can infer that the entity remains static during that interval. To represent both time intervals and time points the concept Time is defined.

$$Time \sqsubseteq TemporalPoint \sqcup Interval \quad (5)$$

In the model, the property hasTime is defined as a domain elements of the class Time. Thus both *TemporalPoints* and *Intervals* can be used.

$$hasTime|_{Time} \sqsubseteq U \quad (6)$$

B. Semantic Trajectories Model Specification

In a perdurantism approach the evolution of an entity is described by a set of transitory constructions called timeslices. They are transitory in the sense that they are valid only for a defined finite time. In our work, the concept of timeslices is represented by the class TimeSlice. This class has four components: 1) Spatial, which is the geometric representation of the feature; 2) Identity, to associate each timeslice to the feature they represent; 3) Temporal, to describe the time in which the timeslice is valid; 4) A set of alphanumeric properties, that describe characteristics of the feature during the timeslice valid time.

Equation 7 depicts the formalization of the class TimeSlice in our research.

$$\begin{aligned} TimeSlice \equiv &\exists hasGeometry.Geometry \sqcap \\ &\exists TimeSliceOf.Feature \sqcap \\ &\exists hasTime.Time \end{aligned} \quad (7)$$

In a geographic area with a dynamic land cover, the same region can be associated with different timeslices at different points of time. In order to represent spatial associations in time, a filiation property is defined in the model. This property enables to link two timeslices of consecutive times. As a result, the class Timeslice should be defined as domain (see Equation 8) and range (see Equation 9).

$$\geq 1 hasFiliation \sqsubseteq Timeslice \quad (8)$$

$$T \sqsubseteq \forall hasFiliation.Timeslice \quad (9)$$

This property is essential to retrieve linkage between two entities. In the model, it is proposed to specialize this property in different layers of knowledge. Equation 10 formalize the hierarchy using Description Logics.

$$hasFiliation \sqsubseteq hasContinuation \sqcup hasDerivation \quad (10)$$

Thus, the temporal domain is seen as a linear structure T composed by a set of temporal points P. The components of P follow a strict order, which forces all points between two temporal points t_1 and t_2 to be ordered. By selecting a pair $[t_1;t_2]$ we can limit a closed interval of ordered points.

Temporal Points:

$$P\ P^I \subseteq \Delta^I \quad (12)$$

The set of interval structures in T is represented by $T^*_<$

Time Intervals :

$$T \overset{*}{<} [t_0, t_f] = \{x \in P | t_0 \leq x \leq t_f, t_0 \neq t_f\} in T \quad (13)$$

In the Continuum Model, t_0 is defined by the datatype property *hasBeginInstant* and t_f is defined by the datatype property *hasEndInstant*. The spatial representation of the timeslice of an object is given through its geometry (G). The semantic component of the timeslice of an object is represented by S. It describes the nature of the entities and can be composed by one or more alphanumeric properties. Finally, a timeslice has an identity held by the property *isTimesliceOf* which connects it to an object (O). Each timeslice (TS) in the model has four components: 1) a time interval ($T^*_<$), 2) a geometry (G), 3) an identity (O) and 4) a semantic component (S) representing all other potential properties associated to a timeslice. We define all these properties using (TS) base symbol, as defined in [62], which stands for the qualities that distinguish a timeslice from another apart from its interval of existence, identity, and its geometry:

(note that S $\equiv$ (TS)):

$$TS \equiv \forall hasGeometry.G \sqcap \forall hasTime.T^*_< \sqcap (\overline{TS}) \sqcap \forall isTimesliceOf.O \tag{14}$$

The qualitative relations in the time domain are based on binary and mutually exclusive relations as proposed by Allen [11].

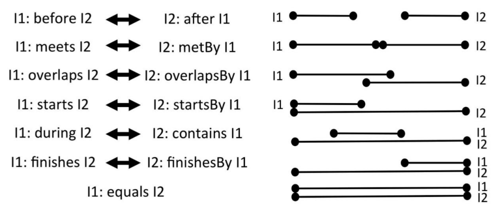

Figure 5. Allen temporal relationships.

In the *Continuum* Model a change on the spatial representation or on the semantic component generates a new object timeslice which has a filiation relationship with the original object timeslice. Additionally, it is well known that the time interval of the parent object timeslice meets the time interval of the child object timeslice. The filiation relationship between timeslice object ts_1 and ts_2 is defined by the relationships between their spatial representations (ts_{1g} and ts_{2g}), their semantic definitions (ts_{1s} and ts_{2s}), their identity (ts_{1o} and ts_{2o}) and their time intervals (ts_{1i} and ts_{2i}). A filiation relationship is defined when a change occurs on the geometry, the semantic component or the identity. The *meets* relationship specifies the time relationship between two between timeslice object ts_1 and ts_2 (w.r.t. fig. 5).

$$\begin{aligned} &\forall hasFiliation.TS\{ts_1 \in TS^I | \forall ts_2.(ts_1, ts_2.(ts_1, ts_2) \in hasFiliation^I \rightarrow \\ &ts_2 \in TS^I \wedge \exists((ts_{1g} \neq ts_{2g}) \vee (ts_{1s} \neq ts_{2s}) \vee (ts_{1o} \neq ts_{2o})) \wedge (meets(ts_{1i}, ts_{2i}))\} \\ &Where: \{ts_1, ts_2\} \in TS, \{ts_{1g}, ts_{2g}\} \in G, \{ts_{1s}, ts_{2s}\} \in S, \{ts_{1o}, ts_{2o}\} \in O, \{ts_{1i}, ts_{2i}\} \in I \end{aligned} \tag{15}$$

C. Spatio-Temporal Relationships Between Timeslices

The STriDE Model Specification consists in defining the spatio-temporal relationships between timeslice objects. The spatial and temporal constraints must be considered to define the hierarchy of possible links between timeslice objects.

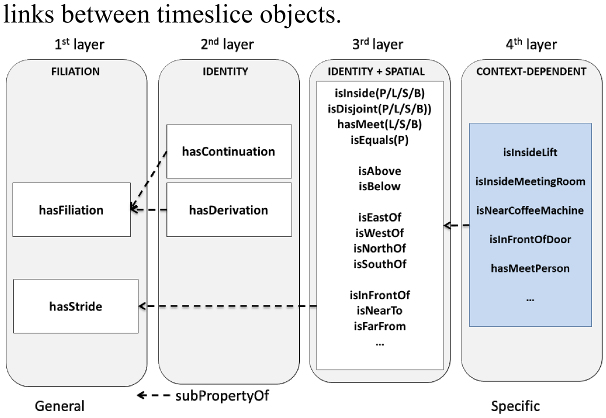

Figure 6. Examples of hasSTRriDE relationships between TimeSlices.

In the fig. 6 the (P/L/S/B) means Point, Line, Surface, Body. A body is a 3D object. In the equation (15), the predicate *meets* must be changed with the other temporal relationships but not by the temporal relationships *before, after, meet or metBy*. It means that any Timeslice object can be linked to another one if they share a time lapse (e.g. fig. 5). However, these relationships are not reflexive and the timeslice object cannot be linked to himself.

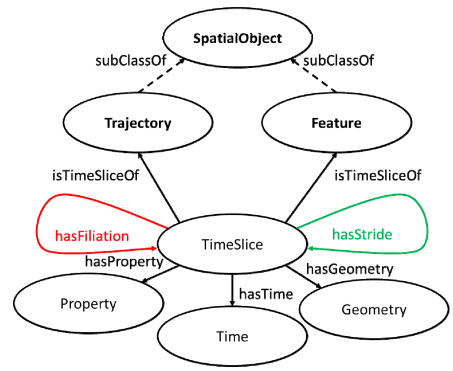

Figure 7. The *hasStride* relationships in the STriDE model.

Figure 7 shows in green the *hasStride* relationships that links two timeslice objects, but not the same one. The hasFiliation relationship is also not reflexive. Due to the lack of space, few details are given about the STriDE model and how the make advantage of this graph and ontology-based model. The language SPARQL can be used to query the model, integrity constraints can qualify the data generated from raw data trajectories, and logic constraints make it possible to infer new knowledge. The figure 8 shows an example of *hasStride* relationships between three STriDEs.

V. Conclusion

The presented research paper tries to emphasize the possibility to link semantic trajectories of moving and changing objects. The data model presented captures moving and changing objects in the context of dynamic built environments. The pre-processing permits to generate semantic trajectories and crossing trajectories formalized in the ontology using *hasStride* links is not presented. This pre-processing is time consuming and required, at the end, space to store the results. The results are even bigger if the granularity is too fine. Consequently, even if solutions such as the Stardog triplestore (http://www.stardog.com/docs/) which can store and infer on more than 50 billion triples, the STriDE data model is verbose. Thus, a high number of tracked items in a large and rich environment can lead to an unusable solution for a long period tracking. The business context is important and should drive the level of detail recorded by the STriDE model and the post-processing on semantic trajectories to capture activities and behaviors of users and objects. In addition, the author is working on how to add vagueness and uncertainty in the Semantic trajectories at the description logics level [51] to capture the imprecision of the localization devices and uncertainty of simplified trajectories.

ACKNOWLEDGMENT

The author would like to thank for their support the Conseil Régional de Bourgogne and the funds provided by the PARI 2015 and 2016.

REFERENCES

[1] E. Almirall, J. Wareham, C. Ratti, P. Conesa, F. Bria, A. Gaviria, A. Edmondson, Smart Cities at the Crossroads: NEW TENSIONS IN CITY TRANSFORMATION. California Management Review, 59(1), 2016, 141-152. doi:10.1177/0008125616683949

[2] J. Wong, H. Li, S. Wang, Intelligent Building Research: a Review, Automation in Construction 14 (1), 2005, 143 – 159

[3] T. A. Nguyen, M. Aiello, Energy intelligent buildings based on user activity: A survey, Energy and Buildings, Volume 56, January 2013, Pages 244-257, ISSN 0378-7788, https://doi.org/10.1016/j.enbuild.2012.09.005.

[4] D. J. Cook, S. K. Das, How smart are our environments? An updated look at the state of the art, Pervasive and Mobile Computing, Volume 3, Issue 2, March 2007, Pages 53-73, ISSN 1574-1192, https://doi.org/10.1016/j.pmcj.2006.12.001.

[5] R. Vanlande, C. Nicolle, C. Cruz, IFC and building lifecycle management, Automation in construction, 2008

[6] C. Parent, S. Spaccapietra, C. Renso, G. Andrienko, N. Andrienko, V. Bogorny, M. L. Damiani, A. Gkoulalas-Divanis, J. Macedo, N. Pelekis, Y. Theodoridis, and Z. Yan. 2013. Semantic trajectories modeling and analysis. ACM Comput. Surv. 45, 4, Article 42 (August 2013), 32 pages. DOI=http://dx.doi.org/10.1145/2501654.2501656

[7] B. H. Albanna, I. F. Moawad, S. M. Moussa, A. M. Sakr, Semantic Trajectories: A Survey from Modeling to Application, Information Fusion and Geographic Information Systems (IF&GIS' 2015): Deep Virtualization for Mobile GIS, 2015, Springer International Publishing, 59-76, 978-3-319-16667-4, 10.1007/978-3-319-16667-4_4

[8] D. Zheni, A. Frihida, A semantic approach for the modeling of trajectories in space and time. In: Advances in conceptual modelling, 2009, pp 347–356

[9] Z. Yan, Semantic trajectories: computing and understanding mobility data In: Ph.D. dissertation, Swiss Federal Institute of Technology, Information and Communication Dept., Lausanne, 2011

[10] Z. Yan, S. Spaccapietra, Towards semantic trajectory data analysis: a conceptual and computational approach. VLDB PhD Work 15(2), 2009, 165–190

[11] Z. Yan, C. Parent, The semantic web: research and applications, vol 6088. Springer, Berlin, 2010, pp 60–75

[12] G. M. Youngblood, D. J. Cook, L. B. Holder, and E. O. Heierman. Automation intelligence for the smart environment. In Proceedings of the International Joint Conference on Artificial Intelligence, 2005.

[13] Y. Zheng, X Zhou, Computing with spatial trajectories. Springer Science & Business Media, 2011

[14] C. Renso, S. Spaccapietra, E. Zimanyi, Mobility Data: Modeling. Management, and Understanding. Cambridge University Press, 2013, 174-193.

[15] B. Harbelot, H. Arenas, C. Cruz, LC3: A spatio-temporal and semantic model for knowledge discovery from geospatial datasets, Web Semantics: Science, Services and Agents on the World Wide Web, Volume 35, Part 1, December 2015, Pages 3-24, ISSN 1570-8268, https://doi.org/10.1016/j.websem.2015.10.001.

[16] B. Harbelot, H. Arenas, and C. Cruz, "Continuum: A spatiotemporal data model to represent and qualify filiation relationships," in Proceedings of the 4th ACM SIGSPATIAL International Workshop on GeoStreaming (IWGS), November 2013.

[17] H. Arenas, B. Harbelot, C. Cruz, A Semantic analysis of moving objects, using as a case study maritime voyages from eighteenth and nineteenth centuries, the Sixth International Conference on Advanced Geographic Information Systems, Applications, and Services, 2014.

[18] B. Harbelot, H. Arenas, C. Cruz. Using Semantic Web Technologies to Follow the Evolution of Entities in Time and Space. International Journal On Advances in Intelligent Systems, Freimut Bodendorf, University of Erlangen-Nuernberg, Germany, pp.256 to 265, 2013.

[19] E. Meskovic, Z. Galic, M. Baranovic, Managing Moving Objects in Spatio-temporal Data Streams, in: Proceedings of the 2011 IEEE 12th, International Conference on Mobile Data Management - Volume 02, MDM '11, IEEE Computer Society, Washington, DC, USA, 2011, pp. 15–18. doi:10.1109 / MDM.2011.44. URL http://dx.doi.org/10.1109/MDM.2011.44

[20] G. Del Mondo, M. A. Rodriguez, C. Claramunt, L. Bravo, R. Thibaud, Modeling Consistency of Spatio-temporal Graphs, Data & Knowledge, Engineering 84 (2013) 59–80. doi:10.1016 / j.datak.2012.12.007. URL http://dx.doi.org/10.1016/j.datak.2012.12.007

[21] G. Del Mondo, J. G. Stell, C. Claramunt, R. Thibaud, A Graph Model for Spatio-temporal Evolution, Journal of Universal Computer Science 16 (11) (2010) 1452–1477.

[22] P. Muller, Topological spatio–temporal reasoning and representation, Computational Intelligence 18 (3) (2002) 420–450.

[23] J. Chen, H. Wu, S. Li, A. Liao, C. He, S. Peng, Temporal Logic and Operation Relations Based Knowledge Representation for Land Cover Change Web Services, ISPRS Journal of Photogrammetry and Remote Sensing 83 (0) (2013) 140 – 150

[24] J. Stell, G. Del Mondo, R. Thibaud, C. Claramunt, Spatio-temporal evolution as bigraph dynamics, Spatial Information Theory (2011) 148–167.

[25] R. Reiter, On closed world data bases, Springer, 1978.

[26] M. P. Armstrong, Temporality in spatial databases, in: Proceedings: GIS / LIS, Vol. 88, 1988, pp. 880–889.

[27] G. Langran, N. R. Chrisman, A framework for temporal geographic information, Cartographica: The International Journal for Geographic Information and Geovisualization 25 (3) (1988) 1–14.

[28] M. F. Worboys, A unified model for spatial and temporal information, The Computer Journal 37 (1) (1994) 26–34.

[29] K. Hornsby, M. J. Egenhofer, Identity-based change: a foundation for spatio-temporal knowledge representation, International Journal of Geographical Information Science 14 (3) (2000) 207–224.

[30] M. J. Egenhofer, K. K. Al-Taha, Reasoning about gradual changes of topological relationships, Theories and methods of spatio-temporal reasoning in geographic space (1992) 196–219.

[31] D. J. Peuquet, N. Duan, An event-based spatiotemporal data model (estdm) for temporal analysis of geographical data, International journal of geographical information systems 9 (1) (1995) 7–24.

[32] C. Claramunt, M. Theriault, Toward semantics for modelling spatio-temporal processes within gis, Advances in GIs Research I (1996) 27–43.

[33] J. Jiang, M. Worboys, Event-based topology for dynamic planar areal objects, International Journal of Geographical Information Science 23 (1) (2009) 33–60.

[34] B. Jiang, C. Claramunt, B. Klarqvist, Integration of space syntax into gis for modelling urban spaces, International Journal of Applied Earth Observation and Geoinformation 2 (3) (2000) 161–171.

[35] B. Jiang, C. Claramunt, A structural approach to the model generalization of an urban street network*, GeoInformatica 8 (2) (2004) 157–171.

[36] B. Jiang, C. Claramunt, Topological analysis of urban street networks, Environment and Planning B 31 (1) (2004) 151–162.

[37] S. Spaccapietra, C. Parent, M. L. Damiani, J. A. Macedo, F. Porto, and C. Vangenot, "A conceptual view on trajectories," Data Knowledge Engineering, vol. 65, no. 1, pp. 75–91, 2008.

[38] Z. Yan, J. Macedo, C. Parent, and S. Spaccapietra, "Trajectory ontologies and queries," Transactions in GIS, vol. 12, no. 1, pp. 75–91, 2008.

[39] Z. Yan, D. Chakraborty, C. Parent, S. Spaccapietra, and K. Aberer, "SeMiTri: A framework for semantic annotation of heterogeneous trajectories," in Proceedings of the 14th. International Conference on Extending Database Technology EDBT 2011, 2011, pp. 259–270.

[40] B. Harbelot, H. Arenas, C. Cruz, A semantic model to query spatial-temporal data, in: V. Popovich, C. Claramunt, M. Schrenk, K. Korolenko (Eds.), Information Fusion and Geographic Information Systems (IF and GIS 2013), Lecture Notes in Geoinformation and Cartography, Springer Berlin Heidelberg, 2014, pp. 75–89. doi:10.1007/978-3-642-31833-7 5.

[41] U. Hustadt, et al., Do we need the closed world assumption in knowledge representation?, in: KRDB, 1994.

[42] H. J. Levesque, The logic of incomplete knowledge bases, in: On conceptual modelling, Springer, 1984, pp. 165–189.

[43] A. Motro, Integrity = validity + completeness, ACM Transactions on Database Systems (TODS) 14 (4) (1989) 480–502.

[44] J. F. Allen, Maintaining knowledge about temporal intervals, Communications of the ACM 26 (11) (1983) 832–843.

[45] F. Baader, W. Nutt, Basic description logics., Description logic handbook (2003) 43–95.

[46] H. Ben Hmida, F. Boochs, C. Cruz, C. Nicolle, "From Quantitative Spatial Operator to Qualitative Spatial Relation Using Constructive Solid Geometry, Logic Rules and Optimized 9-IM Model, A Semantic Based Approach", IEEE International Conference on Computer Science and Automation Engineering (CSAE 2012).

[47] Hmida, H. B., Cruz, C., Boochs, F., & Nicolle, C. (2013). Knowledge base approach for 3d objects detection in point clouds using 3d processing and specialists knowledge. International Journal on Advances in Intelligent Systems, vol 5 no 1 & 2, year 2012.

[48] Boochs, F., Marbs, A., Hmida, H. B., Truong, H., Karmachaiya, A., Cruz, C., ... & Voisin, Y. (2011, March). Integration of knowledge to support automatic object reconstruction from images and 3D data. In Systems, Signals and Devices (SSD), 2011 8th International Multi-Conference on (pp. 1-13). IEEE.

[49] A. Artale, E. Franconi, A Temporal Description Logic for Reasoning About Actions and Plans, Journal of Artificial Intelligence Research, 9 (1) (1998) 463–506.

[50] J. Tao, E. Sirin, J. Bao, D. L. McGuinness, Integrity constraints in owl., in: AAAI, 2010.

M. Unold, C. Cruz, How to Enrich Description Logics with Fuzziness, Computing Conference 2017, 18-20 July 2017 - London, United Kingdom

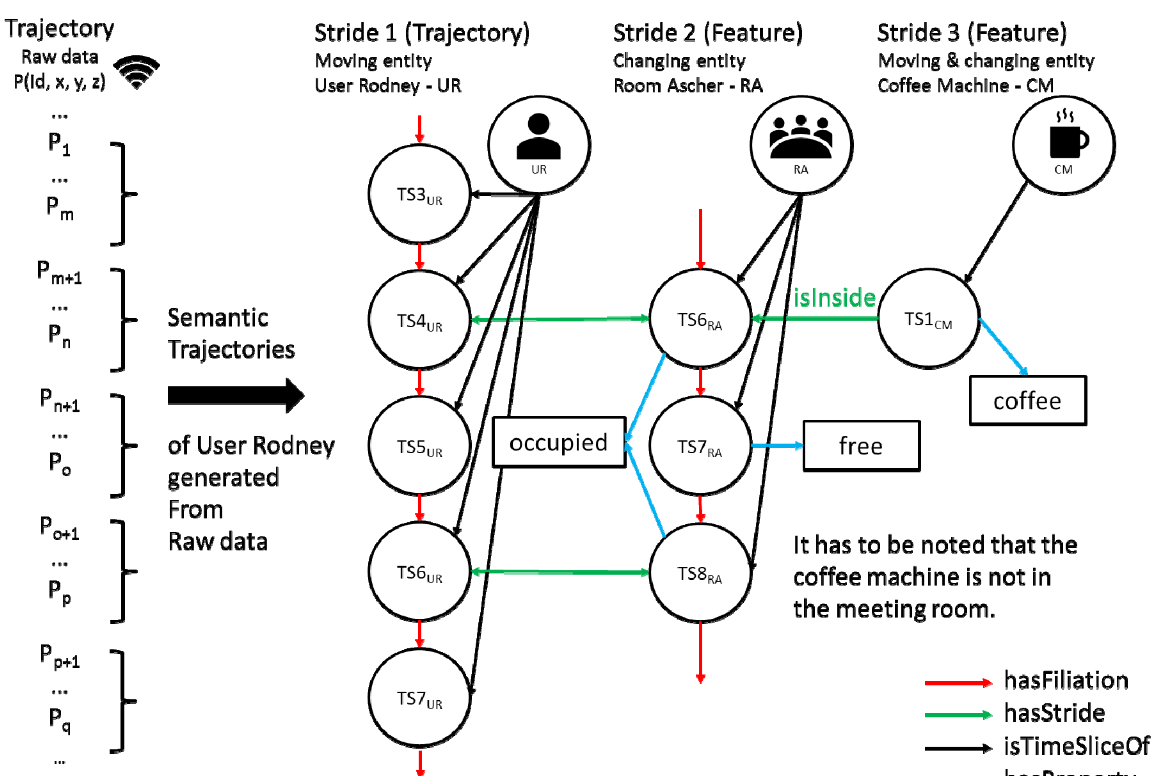

Figure 8. Examples of Strides generated from the user trajectory raw data, the BIM for the building element Room and the coffee machine with a localization device embedded (IoT).