

Knowledge-Driven Method for Object Qualification in 3D Point Cloud Data

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ABSTRACT. The identification of objects in 3D point cloud data has always presented a real challenge. Such a process highly depends on human interpretation of the scene and its objects. Actual approaches are numerical based; in best cases, static models are used as a template for the detection process. By the presented work, we aim at extending the detection process by bringing the human expert knowledge about the scene, the objects, their characteristics and their relations onto the processing chain. To do, we present in this paper a knowledge-driven method for the detection of object and its identification using ontology. The knowledge contained by the ontology is constraints on objects. Logic programs are used as rules to define constraints between objects. The processing of the scene is an iterative annotation process that combines 3D algorithms, geometric analysis, spatial analysis and especially specialist's knowledge. The created platform takes a set of 3D point clouds as input, and produces as output a populated ontology corresponding to an indexed scene. The context of the study is the detection of railway objects materialized within the Deutsche Bahn. Thus, the resulting enriched and populated ontology that contains the annotations of objects in the point clouds, and can be used further on to feed a GIS system or an IFC file for architecture purposes.

Keywords: Knowledge based processing, Semantic qualification, OWL Ontology, 3D spatial knowledge, 3D algorithm knowledge.

1 INTRODUCTION

Through the last years, formal ontologies have been suggested as a solution for several engineer problems. Hence, it has efficiently replaced the standard data bases and relational one by more flexibility and reliability. Well-designed ontologies own lots of positive aspects like those related to defining a controlled vocabulary of terms, inheriting and extending existing terms, declaring a relationship between terms, and inferring relationships by reasoning on existent ones. Ontologies are used to represent formally the knowledge of a domain using graphs and logical structure to make computers able to understand and process it [1]. Recently, the tendency related to the use

of semantic has been explored, where we bring to point the automatic data extraction from 3D point clouds [2], such a data provides a digital model of the surveyed scene. Actually, research on 3D processing has well focused on the investigation of the reconstruction and the recognition of geometrical shapes [3] where two main approach has seen the light [4], the data driven detection and model driven one. While the data driven methods [5] extract geometries from the point cloud and combine them to the final model, model driven method [6] use predefined primitive templates and information as detected geometries from the data to map them against the most likely templates.

In this paper, we present a knowledge driven method standing from the assumption that specialist's knowledge will help the improvement of the automation, the accuracy and the result quality. In contrast to existing approaches, the solution consists in using only prior knowledge about the context and the objects. This knowledge is the basis for a selective knowledge-oriented detection and recognition of objects in point clouds. In this case, knowledge about objects has to include detailed information about the objects' geometry, structure, 3D algorithms, 3D spatial relation, etc. The context of the study is the detection of the railway scene elements. Once detected and annotated, the process enriches and populates the ontology with individuals and properties.

This paper is divided into 6 sections. Section 2 introduces the technical background on the object detection and qualification in 3D point clouds data. Section 3 introduces the used and modeled knowledge. Section 4 deals with the spatial relation qualification process. Section 5 highlights the knowledge guidance for the object qualification process and finally section 6 concludes this paper.

2 RELATED WORK

The technical survey of 3D scene is a long and costly process. It aims to build a digital model by geometric analysis of an existing 3D point clouds data. According to the literature [7], there are two major approaches of object detection and annotation: the model-driven approach and the data-driven one. The data-driven approach, called also as non-parametric modeling approach presents a technique that attempts to model a 3D point clouds scene by a sequence of operations more or less complex, allowing the generation of an information model without relying on a specific library. This field of approaches models a building without taking any consideration of its form. Otherwise, it attempts to model it just based on 3D point clouds as initial data. For instance, first methods have been presented in [8] and concern the automatic extraction of model-driven and prismatic building models from dense digital elevation models generated by photogrammetric techniques or laser scanning. Rusu et al., [9] investigate the following computational problem: given a 3D point cloud model of an environment, how is it possible first to segment the point cloud into sub segments that correspond to relevant objects and then to label the segments with the respective category label. The created system includes two components: the Semantic 3D Object Map which contains those parts of the environment with fixed positions and utilitarian functions

(walls, floor, kitchen appliances, cupboards, tables, etc.), and a Triangulated Surface Map updated continuously. The Semantic Object Map is built by classifying a set of planar regions with estimated 3D geometrical features, and serves as a semantic resource for an assistant mobile personal robot, while the Triangulated Surface Map supports 3D collision detection and path planning routines for a safe navigation and manipulation. The advantages of a model-driven approach are that it provides geometrical models without getting real geometries, since it is based on the calculation of values of parameters. Thus, it is important to underline the high computing speed gained by these approaches in comparison with data-driven ones. Errors in this type of model can come from the calculation of the building parameters values. Moreover, the major disadvantage of a model-driven approach is to be dependent on the buildings types which are available in the building library.

The data-driven approach makes an attempt to model an unspecified building without segmenting it into primitives. It analyzes the building point cloud as a unit, without involving it to a set of parameters. It proposes the use of a series of numerical operations allowing initially generating an unspecified 3D building from the laser data. Despite the possible risks of obtaining warped models, it remains an approach which treats the general cases. In this field, different techniques based on 3D Hough-transform [7] are used to detect roof planes. Others based on the RANdomSAmpling Consensus algorithm [10] are used to detect planes. Similarly, methods using Douglas-Peucker technique [11] propose to construct the facade models before studying the roof construction; so the resulting 3D building model is firstly constructed with plane roofs [7]. One major fall out of these strategies is basically their rigidity since 3D processing algorithms are designed for certain situations. In order to address these drawbacks, a generic flexible solution is required.

The re-evolution of the knowledge techniques under the Semantic Web framework has provided an opening to strategize different arrangements. The idea is to transfer human ability of adapting to new situation as humans have more capacity to adapt to these changes because of our capability to interpret the semantics, to analyze different knowledge domains at the same time and deliver the result. With the technology moving in the direction of knowledge management, we can foresee intelligent object detection and annotation through knowledge technologies. In this context, formal ontology has been suggested as a solution to the problem of 3D objects reconstruction from 3D point clouds [12]. Ontology structure was defined as a formal representation of knowledge used to reason about the entities within that domain, and may be used to describe the domain. Based on similar technology, modeling algorithmic, Spatial relations, geometric and Spatial knowledge within an ontology structure will open the way to significant improvement in the 3D object detection and annotation capability since it will allow as to create a more dynamicity for object detection based on objects geometries and to make more robust the object qualification process. This paper presents a knowledge based detection approach using the OWL ontology language [13], the Semantic Web Rule Language [14], and 3D processing built-ins aiming at combining geometrical analysis of 3D point clouds and specialist's knowledge.

3 OVERVIEW OF THE DEFINED KNOWLEDGE

Description logics (DLs) [15] provide formalization to knowledge representation of real world situations. This means, it should provide the logical replies to the queries of real world situations. The results are highly sophisticated reasoning engines which utilize the expressiveness capabilities of DLs to manipulate the knowledge. Actually, OWL axiom does not cover the full range of expressive possibilities for object relationships that we might find, since it is useful to declare relationship in term of conditions or even rules. These rules are used through different rules languages to enhance the knowledge possess in an ontology. Some of the evolved languages are related to the semantic web rule language (SWRL) [16] and the advanced Jena rules [17]. SWRL is a proposal as Semantic Web rules language, combining sublanguages of the OWL Web Ontology Language [18] with the Rule Markup Language [19]. The SWRL built-ins are keys for any external integration. They help in the interoperation of SWRL with other formalism and provide an extensible infrastructure for knowledge based applications. Actually, Comparisons Built-Ins, Math Built-Ins and Built-Ins for Strings are already implemented within lots of platform for ontology management like protégé[20], Equation1.

$$\text{BoundingBox(?x)} \wedge \text{hasHeight(?x, ?ht)} \wedge \text{swrlb:greaterThan(?ht, 6)} \rightarrow \text{electric_pole(?x)} \quad (1)$$

In the actual work, new 3D Spatial built-in for spatial knowledge are integrated. Finally, we use semantic rules with extended Built-Ins to semantically qualify the detected geometries. It provides first estimations of the objects in the 3D scene. Three main knowledge definitions will cooperate together to construct the core of the knowledge driven method: the Scene knowledge (SK), the Spatial Knowledge (SpK) and finally the 3D algorithmic knowledge (AK), Fig.1.

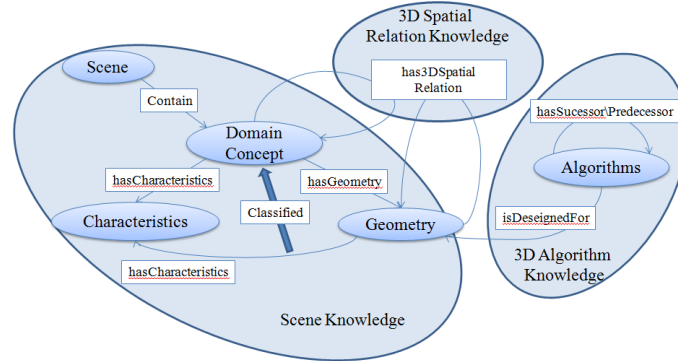


Fig.1. The overview of the general ontology schema

The hierarchical structure of the top level class axioms of the ontology is given in Fig.1, where we find five main classes within other data and objects properties able to

characterize the scene in question. The class axiom DC:DomainConcept which represents the different object found in the target scene and can be considered as the main class in this ontology as it is the class where the target objects are modeled. This class is further specialized into classes representing the different detected object. However, the importance of other classes cannot be ignored. They are used to either describe the object geometry through the Geom:Geometry class axiom by defining its geometric component or the bounding box of the object that indicate its coordinates or to either describe its characteristics through the Charac:Characteristics class axiom. Additionally, the suitable algorithms are automatically selected based on its compatibility within the object geometry and characteristics via the Alg:Algorithm class. Add to that, other classes, equally significant, play their roles in the backend. The connection between the basic mentioned classes is carried out through object and data properties' axioms. The properties' axioms define relationships between classes in the ontology. They are also used to relate an object to others via spatial relations.

Table 1. Example of the knowledge description of a main signal

Object	Geometry	DL Constraints	3D Spatial relations
Electric Born	Vertical Lines	Height: Between 4m and 6m Length: max 0.5 Width: max 0.5 Lines: 1 or 2 Vertical line	Contains: 2parallel lines MUST be connected: to a Small Box Distant: 50m from Electric Born Right side: of the Rail

In more details, scene knowledge (SK) includes information about objects (Domain Concept) as properties, restriction, relationship with other objects (hierarchical relationships), and also about the object's geometry that composes its structure, Table 1. The scene is modeled thought axioms of the DLs and presents the behaviors of objects. For instance, an Electrical born presents a subclass of the Domain Concept one.

$$\text{ElectricPole} \sqsubseteq \text{DomainConcept} \quad (1)$$

Likewise, it is related to class Line_3D (which is a type of class Geometry) through the relationship hasLine3D (subproperty of hasGeometry).

$$\text{Electric Pole} \sqsubseteq \exists \text{hasLine3D. Line_3D} \quad (2)$$

For instance, the following DLs constructor defines the semantic of the "ElectricPole". It means should be a vertical bounding box with a high greater than 5 m, and that contains at least 2 parallel lines.

$$\text{ElectricPole} \sqsubseteq (\exists \text{hasHeight. } \{> 5\} \sqcap \geq 2. \text{hasParallel. Line} \sqcap \text{VerticalBoundingBox})(3)$$

Like seen in Table 1, 3D spatial knowledge already known by a human present a main key for the qualification process since it yield to the objects state disambiguation based on its relation with the common environment. After modeling the different knowledge in the ontology structure, spatial observation will be also modeled. 3D spatial knowledge includes standards like the 3D topological knowledge, 3D metric

knowledge and 3D processing relation knowledge. Each one of the cited spatial relation knowledge contains a variety of relations modeled on the ontology structure. The next table gives an example for topological relation, its name in the ontology using the prefix “swrl_topo”, its semantic characteristics and the new built-in to automatize the computation of relations with the help of SWRL rules. OWL can state that the relations are transitive, symmetric, functional, etc. The topological relationships between objects are created automatically via the SWRLrule calculation process in the ontology. Once a relation has already been computed, then, there is no need to recalculate.

Table 2.Examples of topological relationships and its semantics

Topology	Property name	Semantic property definition	SWRL built-ins
Disjoint	topo:disjoint	Transitive, symmetric, irreflexive	topo:disjoint(?x, ?y)
Contains	topo:contains	Transitive, asymmetric, irreflexive	topo:contains(?x, ?y)

Finally, the understanding that the scene knowledge and its interdependency affect the detection algorithm selection and execution, and yield us to think about the semantics of algorithms and how it would provide an active participation to process the scene. To do, we opt to model algorithms, their attributes and relationships that may exist between them add to the utilisability condition of each one of them. Based on their general purposes, Algorithms classes are classified in upper classes like “Geometrical detection”, “Appearance detection” and “Signal processing”, etc. To specify the algorithm uses case, the axiom “isDesignedFor” is defined in the ontology. The input data type of an algorithm is determined through the “hasInput” object property axiom. Similarly, “hasOutput” axiom defines the output data type of an algorithm after processing. This knowledge is used to generate automatically the sequence of signal processing algorithms depending on the object properties defined previously. This point is out of the scope of the paper, and will not be described. The focus is made on the qualification of objects using topological constraints.

4 QUALIFICATION USING SPATIAL CONSTRAINTS

To maximize the gain from the use of topological knowledge for the object qualification process, spatial relation (Metric, Topologic, Directional and Boolean) between the detected geometries in the knowledge base has be initially qualified. Zlatanova in [20] gives a survey on different 3D models and relations. The spatial operators available for spatial query language consist of 3D Topological operators (disjoint, within, contains, etc.) [21], 3D Metric operators (distance, closerThan, fartherThan, etc.) [22], 3D Directional operators (above, below, northOf, etc.) [23] and finally 3D Boolean operators (union, intersection, etc.) [24]. Topological operators are used to query the topological relationship between two spatial entities. Since most of standard topological operators return a Boolean value, they are also denominated as topological predicates. The use of CSG model[26] and its associated Boolean operator allows us to

model the topological relationships. In order to combine SWRL rules with topological operators, new built-ins are defined in order to compute the operator. Consequently, the results of the operators can be used to define queries or enrich the ontology with new topological relationships between two objects. The following rule specifies that a “Building” defined in the ontology that overlaps a “Railway” defined as well in the ontology, is a “RailStation”.

$$\text{Building}(?b) \wedge \text{Railway}(?r) \wedge \text{topo: overlaps}(?b, ?r) \rightarrow \text{RailStation}(?b) \quad (4)$$

5 KNOWLEDGE-DRIVE QUALIFICATION PROCESS

The ontology schema holds the semantics of the objects like the nature of geometries that objects possess from one side and its 3D spatial relations from another side. The detected geometries could be inferred to initiate the object qualification; such a qualification is provided through the semantic annotation. It is done via semantic rules to semantically annotate the object. These rules are executed through the extended SWRL with Spatial built-Ins. It is also possible to use rules to define new characteristics through SWRL. The example below will annotate detected Bounding Box as objects of the class Electric pole if these bounding boxes are higher than 6m.

$$\text{BoundingBox}(?x) \wedge \text{hasHeight}(?x, ?ht) \wedge \text{swrlb:greaterThan}(?ht, 6) \rightarrow \text{ElectricPole}(?x) \quad (5)$$

The domain ontology schema now hosts the semantically annotated geometries.

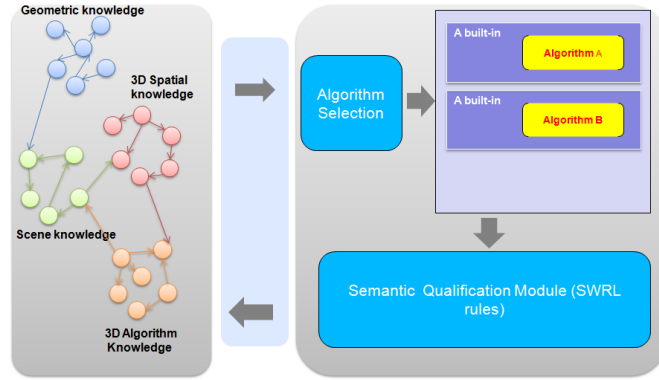


Fig.2. The Knowledge-Driven strategy applied to the 3D point cloud data

Fig.2 illustrates the strategy applied to the 3D point cloud through the control of prior knowledge about the scene, the spatial relations and the 3D processing algorithmic ones to yield geometries that are ready for semantic annotations. First, a set of processing algorithms are selected based on the nature of target objects. Once executed, SWRL rules and DLs constraint are used to qualify the detected geometry. The suggested strategy presents a new semantic based method and aims to adjust the geometry qualification by affecting the right label to each detected object. Actually,

Knowledge about the scene, its geometry, 3D spatial relations and Algorithms will guide the detection and the recognition strategy. Otherwise, it will determine which eventual knowledge can be expected and then detected via the processing algorithms. The presented approach is materialized via an iterative process. It aims to detects and refines detection through new gained knowledge at every step of the iteration, Fig.3. At the core of the first iteration, the railway scene is almost characterized by vertical linear structure. Such information can control the processing, where algorithms designed for such type of geometry will be selected and executed. Based on SWRL rules enriched with the created 3D spatial Built-Ins, a detected and populated geometry can be initially qualified as a Signal and an electrical Born for example, Fig.3. Such a first assumption will help us to detect more discriminant characteristics guiding us to the final classification. During advanced iterations (Second iteration in this case), more focus and precise geometry are detected and populated in the knowledge base through the enhanced knowledge once the previous iteration is achieved. It relies on the ability of the knowledge base to extract the discriminant characteristics that can help the final annotation process. Assuming that the main difference between the two above mentioned semantic object is the existence or not of perpendicular/parallel lines, such a new generated knowledge will verify such information. In case of the existence of perpendicular lines, detected object will be finally classified as an electrical born, Fig.3. In other scenarios, geometric knowledge is not sufficient for the qualification process. Spatial relationships between detected geometries are helpful to manage the qualification process, equation 5. Following such a strategy, iterations will continue until most of ambiguous and unknown object will be qualified.

$$\begin{aligned}
 &\text{MainSignal(?y) } \wedge \text{BoundingBox(?x) } \wedge \text{hasHeight(?x, ?h) } \wedge \text{swrlb:greatThan(?h, 4) } \wedge \\
 &\text{swrlb:lessThan(?h, 6) } \wedge \text{3D_swrlb_Topology:distance(?x, ?y, 1000, 10) } \\
 &\rightarrow \text{DistantSignal(?x)}
 \end{aligned} \tag{6}$$

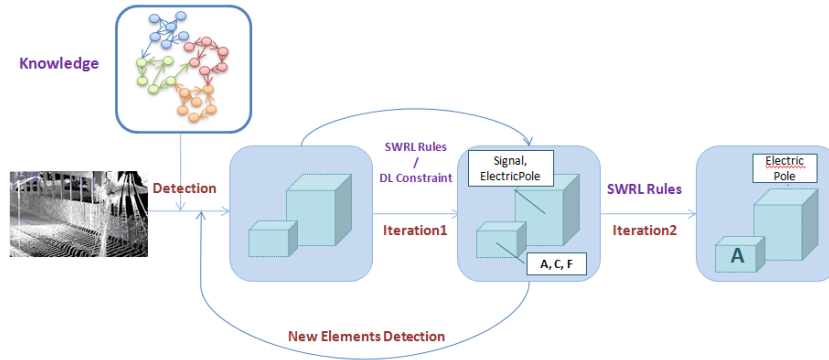


Fig.3. Knowledge Driven method for Object Detection and Qualification Process

5.1 Results

For the approval of the suggested knowledge driven method, 500 m from the scanned point clouds of the Nürnberg railway main station was extracted where we can expect many objects, both complex and simple. After execution, there were 105 geometries detected and among them 34 are annotated 13 as Electric Pole, 3 as Electric box, and 18 as signal. The rest of 71 detected geometries presents especially some noise on the ground where the annotation process was able to discriminate real element from the false one.

Table 3.Detection and annotation results

	Electric pole	Signal	Electric pole
Annotated	13	18	3
Truth data	12	20	5

6 Conclusion

We have presented a comprehensive system for the 3D object detection and annotation process. Contrary to the standard approach, our knowledge driven methods rely more on knowledge engineering capability and as results minimize the human intervention. It include four main components namely the Knowledge base, the 3D processing algorithm, the 3D Spatial relation and Finally the qualification process. The scene index is built by detecting different geometries and annotating them via the extended SWRL rules. The developed Java platform provide an efficient demonstration tools taking a set of 3D point clouds within an empty OWL knowledgebase as input and produce a populated ontology with the detected object.

In the next short time, we plan empowering our knowledge base with more robust DLs constraint and especially the quality knowledge modeling allowing more secure qualification. In parallel, future work consist of making new tests with completely different environment materialized via the airport scene where we plan to relay more on 3D spatial knowledge to qualify the different building elements.

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