FROM 3D POINT CLOUDS TO SEMANTIC OBJECTS
An Ontology-based Detection Approach

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Abstract: This paper presents a knowledge-based detection of objects approach using the OWL ontology language, the Semantic Web Rule Language, and 3D processing built-ins aiming at combining geometrical analysis of 3D point clouds and specialist's knowledge. This combination allows the detection and the annotation of objects contained in point clouds. The context of the study is the detection of railway objects such as signals, technical cupboards, electric poles, etc. Thus, the resulting enriched and populated ontology, that contains the annotations of objects in the point clouds, is used to feed a GIS systems or an IFC file for architecture purposes.

1 INTRODUCTION

As object reconstruction is an important task for many applications, considerable effort has already been invested to reduce the impact of time consuming, manual activities and to substitute them by numerical algorithms. Actually, the automatic processing of 3D point clouds can be very fast and efficient, but often relies on significant interaction of the user for controlling algorithms and verifying the results. Alternatively, the manual processing is intelligent and very precise since a human person uses its own knowledge for detecting and identifying objects in point clouds, but it is very time-consuming and consequently inefficient and expensive. In this context, we aim at inserting business knowledge in automatic detection and reconstruction algorithms in order to make the point cloud processing more efficient and reliable.

Consequently, the WiDOP project (knowledge based detection of objects in point clouds) aims at making a step forward. The goal is to develop efficient and intelligent methods for an automated processing of terrestrial laser scanner data. In contrast to existing approaches, the project consists in using prior knowledge about the context and the objects. This knowledge is extracted from databases, CAD plans, Geographic Information Systems (GIS), or domain experts. Therefore, this knowledge is the basis for a selective knowledge-oriented detection.

The following paper is structured into section 2 which gives an overview of actual existing strategies for reconstruction processes, section 3 explains the general adopted architecture and the related ontology structure, section 4 describe the domain knowledge modelling, section 5 highlight the annotation process, section 6 gives first results for a real example and section 7 concludes and shows next planned steps.

2 BACKGROUND

This section is composed of two parts. This first part deals with the detection strategies described in the literature for geometric modelling and object recognition. The second part presents the knowledge modelling which of value for our strategy.

2.1 Detection Strategies

Today, scene model creation process is largely a manual procedure, which is time-consuming and subjective. While there is a clear need for

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automated, or even semi-automated methods to ease the creation of as-built scene, research on the subject is still in the very early stages. This survey shows that many of the existing methods for geometric modelling and object recognition can be important for the process automation. Within the literature, three main strategies are described where the first one is based on human interaction with provided software's for point clouds classifications and annotations. While the second strategy relies more on the automatic data processing without any human interaction by using different segmentation techniques for features extraction. Finally, new techniques present an improvement compared with the cited ones by integrating semantic networks to guide the reconstruction process.

2.1.1 Manual Supported Strategy

Actually, tools used for 3D reconstruction of objects are still largely relying on human interaction. Here the user might be supported in his construction activity, but object interpretation, selection and extraction of measurements has to be done manually. That's why this processing is the most time consuming way to come from a data set to extracted objects (Leica Cyclone: 3D Point Cloud Processing Software).

2.1.2 Semi-automatic and Automatic Strategy

These methods present a real optimization within the process compared of the manual ones. Within the current section, we will not expose the problematic from the automatism point of view, but these methods are based on two main parts, geometry extraction and annotation.

Basically, geometry extraction presents the process of constructing a simplified representation of a 3D shape such as a Signal or an Electric born like in our case. The representation of geometric shapes has been studied extensively, (Campbell & Flynn, 2001). Once geometric elements are detected and stored via a specific presentation, the second core of the object detection and scene reconstruction is object recognition, In fact, it presents the process of labelling a set of data points or geometric primitives extracted from the data with a named object or object class. Whereas the geometry modelling task would find a set of points to be a vertical Bounding Box, the recognition task would label that Box as a Signal. Object recognition algorithms may label object instances of an exact shape, or they may recognize classes of objects. Research on recognition of specific building components is still in its early stages. Methods in this category are typically shape-based ones. They aim at segmenting a scene into planar regions, for example, and then use features derived from the segments to recognize objects. This approach was carried out by Rusu et al. by using heuristics to detect walls, floors, ceilings, and cabinets in a kitchen environment, (Rusu, 2008). A similar approach was proposed by Pu and Vosselman to model building façades, (Pu, 2009). One of the challenges of recognition in the building context is that many of the objects to be recognized are very similar to objects of little relevance. Some researchers have proposed qualifying the spatial relationships between objects or geometric primitives to reduce the ambiguity of recognition results. Such approaches generate semantic labels of geometric primitives, and test the validities of these labels with a spatial relationship knowledge base. Usually, such a knowledge model is represented by a semantic network, (Nuchter, 2008). For instance, a semantic net may specify the relationships between entities such as “floors are orthogonal to walls and doors, and parallel with ceilings”. Such validity checking approaches provide ways to integrate domain knowledge into the object recognition process. Another approach for recognition is to first detect objects that are easily recognizable, and then use the context of these initial detections to facilitate recognition of more challenging structures. For example, Pu and Vosselman use characteristic features, such as size, orientation, and relationships to other prominent objects, to detect walls and roofs (Pu, 2009). Then, a second stage detects windows within each of the detected walls.

One strategy for reducing the search space of object recognition algorithms is to utilize knowledge about a specific facility, such as a CAD model or floor plan of the original design. For instance, Yue et al. overlay a design model of a facility with the as-built point cloud to guide the process of identifying which data points belong to specific objects and to detect differences between the as-built and as-designed condition (Yue, 2006). In such cases, object recognition problem is simplified to be a matching problem between the scene model entities and the data points. Another similar approach is presented in (Osche, 2008).

From the above mentioned works, we can deduce that the problematic of 3D object detections and scene reconstructions including standard algorithm and semantic networks can produce first results. Moreover such strategies suffer from the lack of flexibility, efficiency and are in general hard coded. Thus, the context and the algorithm which are part of knowledge that are required to be used in recognition process have to be modelled.

2.2 Knowledge Modelling

In recent years, formal ontology has been suggested as a solution to the problem of 3D objects reconstruction from 3D point clouds (Cruz et al., 2007). In this area, ontology structure was defined as a formal representation of knowledge by a set of concepts within a domain, and the relationships between those concepts. It is used to reason about the entities within that domain, and may be used to describe the domain. Conventionally, ontology presents a "formal, explicit specification of a shared conceptualization" (Gruber, 2005). Ontology provides a shared vocabulary, which can be used to model a domain. Through technologies known as Semantic Web, most precisely the Ontology Web Language (OWL) (MacGuiness and Harmelen, 2004), researcher are able to share and extends knowledge through the scientific community. The basic strength of formal ontology is their ability to reason in a logical way based on Description Logics DL. Lots of reasoners exist nowadays like Pellet (Sirin et al., 2007), (Tasrkov and Harrocks, 2006) and KAON (U. Hustadt, 2010). Despite the richness of OWL's set of relational properties, the axioms 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) and advanced Jena rules (Carroll et al., 2004). SWRL is a proposal as a Semantic Web rules language, combining sublanguages of the OWL Web Ontology Language with the Rule Markup Language (Horrocks et al., 2004). In addition, SWRL language specifies also a library for mathematical built-ins functions which can be applied to individuals. It includes numerical comparison, simple arithmetic and string manipulation.

In this project, domain ontologies are used to define the concepts, and the necessary and sufficient conditions that define the concepts. These conditions are of value, because they are used to populate new concepts. For instance, the concept “Horizontal_BoudinBox” can be specialized into “Wall” if it contains a “Window”. Consequently, the concept “Wall” will be populated with all “Horizontal_BoudinBox” if they are linked to a “Window” or “OpeningElement” object (Vanland, 2008). In addition, the rules are used to compute more complex results such as the topological relationships between objects. For instance, the intersection of two objects is used to determine if a part of an object is inside of another object. The ontology is than enriched with this new relationship. The topological relation built-ins are not defined in the SWRL language. Consequently, the language was extended.

3 APPROACH OVERVIEW

This paper presents a knowledge based detection approach using the OWL ontology language, the Semantic Web Rule Language, and 3D processing built-ins aiming at combining geometrical analysis of 3D point clouds and specialist’s knowledge. This combination allows the detection and the annotation of objects contained in point clouds. The field of the Deutsch Bahn railway scene is treated for object detection. The objective of the system consists in creating, from a set of point cloud files, from an ontology that contains knowledge about the DB railway objects, and from the knowledge about 3D processing algorithms, an automatic process that produces as output a set of tagged elements contained in the point clouds.

The process enriches and populates the ontology with individuals and relationships between these new individuals. To represent these objects, a VRML file (VRML Virtual Reality Modeling Language, 1995) is generated. The resulting ontology contains enough knowledge to feed a GIS system, and to generate IFC file (IFC Model, 2008) for CAD software, but this is out of the scope the paper. The processing steps can be detailed within the schema of Figure 1, where three main steps aim at detecting and identifying objects.

(3) From 3D point clouds to geometric elements.

(4) From geometry to topologic relations.

(5) From geometric and/or topologic relations to semantic elements annotation.

As intermediate steps, the different geometries within a specific 3D point clouds are detected and stored within the ontology structure. Once done, the existent topological relations between the detected geometries are qualified and then stored within the same knowledge base. Finally, detected geometries are annotated semantically, based on existing knowledge's related to the geometric characteristics and topologic relations.

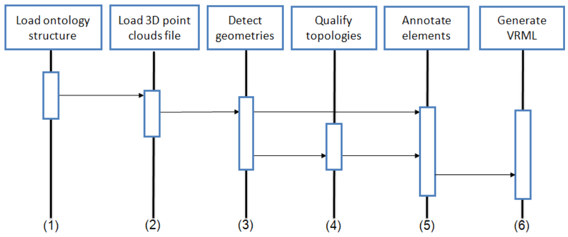

Figure 1: Sequence of the object detection application.

4 DOMAIN KNOWLEDGE MODELLING

The domain ontology presents the core of WiDOP project and provides a knowledge base to the created application. The global schema of the modelled ontology structure offers a suitable framework to characterize the different Deutsche Bahn elements from the 3D processing point of view.

The created knowledge base related to the Deutsche Bahn scene has been inspired next to our discussion with the domain expert and next to our study based on the official Web site for the German rail way specification "http://stellwerke.de". The input ontology contains knowledge about the DB railway objects and knowledge about 3D processing algorithms. Consequently, the knowledge base is divided into two layers, the layer of DB object description and the layer of the algorithmic description.

The sub-layer of scene knowledge is composed by three main classes which are the Scene, the domain concepts and the characteristics. In case of Deutsche Bahn scene, this might comprise a list such as: {Signals, Mast, Schalanlage, etc.}. Besides, the importance of the other classes cannot be ignored.

The sub-layer of the geometrical knowledge formulates the basic geometrical elements used within the prototype. Actually, the annotation elements step processes bounding boxes. Other geometries especially lines and planes are more used to characterize domain concepts elements by a list of geometries. This information is used to create useful descriptions that facilitate the object detection process. The sub-layer of the topologic knowledge represents topological relationships between scene elements. For instance, a topological relation between a distant signal and a main one can be defined, as both have to be distant of 1 Km. The qualification of topologic relations into the semantic framework is done by means of topological Built-Ins called "3DSWRL_Topologic_Built-Ins". Further, the object properties are also used to link an object to others by a topologic relation. In general there are a set of object properties in the ontology which have their specialized properties for the specialized activities, Figure 2.

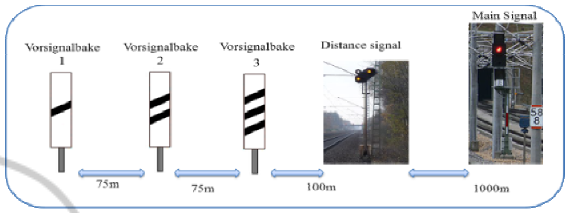

Figure 2: Topologic rules.

Finally, the 3D processing algorithmic layer contains all relevant aspects related to the 3D processing algorithms. It´s integration into the semantic framework is done by means of special Built-Ins called "Processing Built-Ins". They manage the interaction between above mentioned layers. In addition, it contains algorithm definitions, properties, and geometries related to the each defined algorithms.

An importance achievement is the detection and the identification of objects which has linear structure such as signal, indicator column, and electric pole, etc., through utilizing their geometric properties. Figure 3 demonstrates the general layout schema of the ontology.

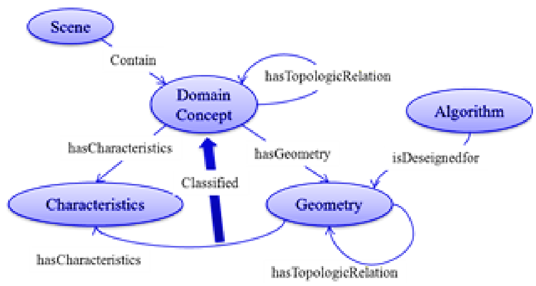

Figure 3: Ontology general schema overview

The next section introduces an overview of the approach undertaken in the WiDOP project to detect and annotate semantically the different Deutsch Bahn objects.

5 SEMANTIC ANNOTATION PROCESS

It presents the process of affecting a semantic label to the different geometries based on SWRL rules and composed by three basic steps.

5.1 Point Cloud to Geometry

The first step aims at the geometric elements detection. Thus, Semantic Web Rule Language within extended built-ins for complex 3D processing are used in order to detect geometry (e.g. Table 1). Once done, the detected elements are used to populate the ontology.

The "3Dswrlb:VerticalElementDetection" built-ins aims at the detection of vertical elements.

The prototype of the designed Built-in is:

```
3D_swrlb_Processing:
VerticalElementDetection(?Vert, ?Dir)
```

where the first parameter presents the target object class, and the last one presents the point clouds directory defined within the created scene. Table 1 show the mapping between the 3D processing built-ins, which are computer and translated to predicate, and the corresponding class.

Table 1: 3D processing built-Ins mapping process.

Processing Built-Ins	*Correspondent class*
3D_swrlb_Processing: VerticalElementDetection(?Vert,?Dir)	Vertical_BoundingBox(?x)

5.2 Geometries to Topology

Once geometries are detected, the second step, aims at verifying certain topology properties between detected geometries. Thus, 3D_Topologic built-ins have been added in order to extend the SWRL language. Topological rules are used to define constrains between different elements. After parsing the topologic built-ins and its execution, the result is used to enrich the ontology with relationships between individuals that verify the rules. Similarly to the 3D processing built-ins, our engine translates the rules with topological built-ins to standard rules, Table 2.

Table 2: Example of topologic built-ins.

Processing Built-Ins	*Correspondent object property*
3D_swrlb_Topology:Intersect(?x, ?y)	Intersect (?x,?y)

5.3 Geometry and/or Topology to Semantic

After the geometry and the topological relation detection, swrl rules aim at qualifying and annotating the different detected geometries. The following example shows how a rule specifies the class of a VerticalElement which is of type Mast regarding its altitude. The altitude is highly relevant only for this element.

```
3DProcessing_swrlb:VerticalElementDetec
tion(?Vert, ?dir) ^ altitude (?x, ?alt)
^swrlb:moreThan (?alt, 6) → Mast
(?Vert)
```

In case where geometric knowledge is not sufficient, the topologic relationships between detected geometries are helpful to manage the annotation process. The following example shows how semantic information about existing objects is used conjunctly with topological relationships in order to define the class of another object.

```
Mast (?vert1) ^ VerticalBB (?Vert2) ^
hasDistanceFrom (?vert1,?vert2, 50) →
Mast(?vert2)
```

6 CASE STUDY

For the demonstration of our system, 500 m from the scanned point clouds related to Deutsch Bahn scene in the city of Nürnberg was extracted. The whole scene has been scanned using a terrestrial laser scanner fixed within a train, resulting in a large point cloud representing the surfaces of the scene objects.

Different swrl rules are processed. First, all vertical elements will be searched in the area of interest, and then topological relations between detected geometries are qualified. To do, useful topologies for geometry annotation are tested. Topologic Built-Ins like `isConnected`, `touch`, `Perpendicular`, `isDistantfrom` are created. As result, relations found between geometric elements are propagated into the ontology, serving as an improved knowledge base for further processing and decision steps.

The last step consists in annotating the different geometries. Vertical elements of certain characteristics can be annotated directly. In more sophisticated cases, the combination of semantic information and topologic ones can deduce more robust results by minimizing the false acceptation rate. Finally, based on a list of SWRL rules, most of detected geometries are annotated. In this example, among 67 elements are classified as Masts, 21 SchaltAnlage, 34 basic signals and finally, 155 secondary signals, Figure 4.

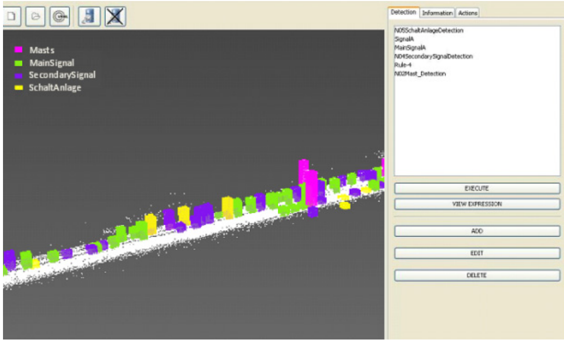

Figure 4: Detected and annotated elements visaliazation within VRML language.

7 CONCLUSIONS

We have proposed a new solution to perform the detection of objects from technical survey within the laser scanner technology. The solution performs the detection of objects in 3D point clouds by using available knowledge about a specific domain (DB). This prior knowledge modelled within ontology SWRL rules are used to control the 3D processing execution, the topologic qualification and finally to annotate the detected elements in order to enrich the ontology and to drive the detection of new objects.

Future work will include the integration of new knowledge's that can intervene within the annotation process like the number of detected lines within each bounding box and the update of the general platform architecture, by ensure more communication between the scene knowledge within the 3D processing.

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