Semantic-based Technique for the Automation the 3D Reconstruction Process

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***Abstract*—The reconstruction of 3D objects based on point clouds data presents a major task in many application field since it consumes time and require human interactions to yield a promising result. Robust and quick methods for complete object extraction or identification are still an ongoing research topic and suffer from the complex structure of the data, which cannot be sufficiently modeled by purely numerical strategies. Our work aims at defining a new way of automatically and intelligently processing of 3D point clouds from a 3D laser scanner. This processing is based on the combination of 3D processing technologies and Semantic Web technologies. Therefore, the intention of our approach is to take the human cognitive strategy as an example, and to simulate this process based on available knowledge for the objects of interest. First, this process introduces a semantic structure for the object description. Second, the semantics guides the algorithms to detect and recognize objects, which will yield a higher effectiveness. Hence, our research proposes an approach which uses knowledge to select and guide the 3D processing algorithms on the 3D point clouds.**

Keywords - Semantic web; knowledge modeling; ontology; 3D processing; mixed strategy; 3D scene reconstruction; object identification

I. INTRODUCTION

The laser scanning technology is a powerful tool for many applications; it has partially replaced traditional surveying methods since it can speed up field work significantly. This results in rich datasets with lots of useful and useless information. On one hand, the "manual" processing of such data set is efficient and robust since a human uses his own knowledge for detecting and identifying objects in point clouds, but this process is tedious, time-consuming and expensive. On the other hand, the "automatic" processing of 3D point clouds can be very fast and efficient, but often it relies on significant interactions with the user for controlling algorithms and verifying the quality of the results. The WiDop project [24] aims at the automatic processing of 3D point clouds using the specialist knowledge in order to guide the reconstruction process. By this way, the point clouds quantification and qualification will not be processed via an intermediary step allowing the human intervention (Figure 1). The principle of the WiDop project is a knowledge-based detection of objects in point clouds for AEC (Architecture, Engineering and Construction) engineering applications.

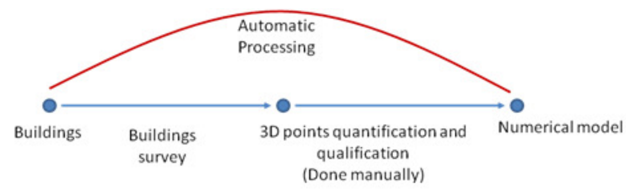

Figure 1. Automatic processing compared to the manual one.

Funded by the German government, the partners of the WiDop project are the German railway company (Deutsche Bahn), the Fraport company (Frankfurt Airport manager), and the Metronome company specializing in 3D point cloud processing. The Fraport company main concerns are building and furniture management of the airport. The furniture's position relative to the security gates and the trashes are constantly moving. In addition, updates are done on buildings such as new walls, destruction of walls, new holes in a wall, new windows, etc. This could be undertaken by the director of a new shop or by the technical employers in order to reorganize storerooms for instance. As a matter of fact, it is very difficult to keep up to date the plans of the airport. The motivation of the Deutsche Bahn Company is the management of railway furniture. The issue is closed to the Fraport Company because they have to face the management of the furniture which changed constantly. The cost of keeping these plans up to date is increasing. The solution consists to fix on a locomotive a 3D terrestrial laser scanner and to survey the surrounding landscape. After the first survey, the resulting data will be considered as a reference for comparisons with future surveys in order to detect changes. As a consequence, both companies will benefit from an automatic processing, because too much data has to be processed, and the amount of data leads to a tremendous management cost.

Ten years ago, a new format, which seems to be very suitable for our purpose was developed by the IAI (The International Alliance for Interoperability) it is named the IFC format (IFC - Industry Foundation Classes). The specification is a neutral data format to describe exchange and share information typically used within the building and facility management industry. This norm considers the building elements as independent objects where each object is characterized by a 3D representation and defined by a semantic normalized label. Consequently, the architects and the experts are not the only ones who are able to recognize the elements, but everyone will be able to do it, even the system itself. For instance, an IFC door is not just a simple collection of lines and geometric primitives recognized as a door; it is an “intelligent” object door which has a door attributes linked to a geometrical definition. The building mock-up for instance is designed by engineers and it describes all concrete and abstract elements of a building. Thus, it allows each participant in a building project to share and exchange information with the standardized description. IFC files are made of objects and connections between these objects. Object attributes describe the “business semantic” of the object. Connections between objects are represented by “relation elements” [1]. This format and its semantics are the keystone of our solution.

The following section covers background information on works and projects that aim at the reconstruction of 3D scenes from 3D point clouds. Section 3 presents a summary of the designed solution. Section 4 describes in detail the WiDop project. Section 5 focuses on the general model conception and the interaction management between the different created layers. It gives an overview of the different components of the reconstruction process and the basic theory of the "WiDop mixed strategy" presented by the combination of semantic web technology and 3D processing algorithms. Finally, conclusions and suggestions for future work are presented.

II. RELATED WORK

The reconstruction of 3D scene covers a wide area of computer vision; such reconstruction is based on the 3D processing algorithm extracted from the signal processing domain. Recent works aims to reconstruct a scene based on semantic networks describing the relationship between the scene objects. Based on these observations, this section will be articulated in two parts: the first one presents reconstruction methods based on signal processing algorithms while the second one describe methods based on semantic networks technology. Within a photogrammetric domain, there are three classes of methods for 3D scene reconstruction: Manual, semi-automatic and automatic methods.

A. *3D Processing Methods*

Within the Terrestrial Scanning Laser (TSL) processing, three different main method classes are identified. These methods are classified based on their automatic rate. This section is articulated in three parts. The first part presents re-construction methods based on manual processing of 3D point of clouds. The second presents the semantic based method to assist in the 3D scene reconstruction process and finally, the third one shows the automatic processing methods.

1) Manual methods: are completely based on user interactions. Such methods allow the user to extract the scene elements, which are then converted into 3D models with the help of software’s packages.

2) Semi-automatic methods: in these methods, the user initializes the process by some manual measurements based on which an algorithm tries to extract other elements. Such methods are based on user interactions and automatic algorithm processing. They support elements projection, affine, and Euclidean geometries [2] for the definition of constraints. When modeling buildings by constructive solid geometry, buildings can be regarded as compositions of a few components with simple roof shapes (such as flat roofs, gable roofs and hip roofs). In [3], Vosselman et al. tried to reconstruct a scene based on the detection of planar roof faces in the generated point clouds based on the 3D Hough transform. The used strategy relies on the detection of intersection lines and height jump edges between planar faces. Once done, the component composition is made manually.

3) Automatic methods: these methods are processed without the need of any kind of user intervention. Manual methods have been established with the appearance of the need to reconstruct 3D scene long time ago and are available under a high end commercial feature c.f. Leica® [18] or low cost software Dista [16]. Automatic methods use various approaches but all are based on segmentation techniques to extract features. The methods of Pollefeys et al. [4] and Zisserman et al. [5] use the projective geometry technique. Pollefeys method divides the task of 3D modeling into several steps. The system combines various algorithms from computer vision, like projective reconstruction, auto-calibration and depth map estimation. The disparity calculation between point pairs makes it possible to get a depth map. The depth map is then transformed into a volume model composed of voxels. The surface estimation between the outer surface voxels and the interior surface voxels makes it possible to combine inner and outer object parts. The method developed is effective and obtains good results. The approach of Zisserman et al. [5] proceeds in two steps. First, a coarse surface model of the building is carried out. Then the coarse model guides the search of details (windows and doors) and refines the surface model. The reconstruction uses the detection of “vanishing points”, line correspondence, and the estimation of points and homologous lines. Vanishing points are necessary for the detection of planar primitives with the help of the plane-sweeping method. This method has strong constraints as it contains three perpendicular dominant directions.

B. *Knowledge-based Methods*

All the strategies outlined below are based on signal processing algorithms, in the other side, new strategies appeared recently. They are based on semantic networks to guide the reconstruction like the work of Cantzler et al. [9], it aim to improve the structural quality of a 3D model. Architectural features like orientation of wall are used. Then, the feature's relationships are automatically extracted using a semantic network of the building mock 'up. The whole strategy consists of three steps: the architectural feature extraction from triangulated 3D model. Then the automatic extraction of constraint out of the scene is carried out by matching the planes against a semantic network of the building mock 'up by backtracking research tree. In this step, the semantic network concentrates the definition of the 3D objects and the relationships between them. The constraints such as parallel or perpendicular wall are exploited. The last step consists in applying the constraint to the model. Consequentially, the original model will be fitted to the new constraint model. Ansgar et al. [6] presents a new concept for the building reconstruction. Building model is reconstructed based on it is topology using Markov model technique. Stephane et al. [7], investigates this work into a model based reconstruction of complex polyhedral building roofs. The roof in question is modeled as a structured collection of planar polygonal faces. The modeling is done into two different regimes, one focus on geometry, whereas the other is rules by semantics. Concerning the geometry regime, the 3D line segments are grouped into planes and furthers into faces using a Bayesian analysis. In the second regime, the preliminary geometric model is subject to a semantic interpretation. The knowledge gained in this step is used to infer missing parts of the roof model (by invoking the geometric regime once more) and to adjust the overall roof topology.

C. Discussion

The problem of automatic object reconstruction remains a difficult task to realize in spite of many years of research [8]. The major problems are the impact of the viewpoint onto the appearance of the object, resulting in changes with respect to geometry, radiometry, and existence of occlusions and the lack of texture. Strong variations in the viewpoint may destroy the adjacency relations of points, especially when the object surface shows considerable geometrical variations. This dissimilarity causes confusions within correspondence determination and is even worse, when partial occlusions result in a disappearance of object parts. In cases of weak texture, algorithms do not have sufficient information to correctly solve the correspondence problem. Consequently, the reconstruction fails to give a solution. Cantzler et al. [9] and Nüchte et al. [10] tried to solve these problems by using semantic information coupled to a scene.

Planes found in the reconstruction phase are introduced into a semantic interpretation, which has to fit to a network model [11]. A tree of "backtracking" allows the finding of the best mapping between the interpretation of the scene and the semantic network model. A coherent labeling exists, if all surfaces are labeled. Relations between the nodes of the semantic network are used to define geometrical constraints between labeled surfaces. The model used and the relations between the elements of the model define the knowledge of a typical architectural scene. The interpretation of the scene then forms a semantic network, which is an instance of the architectural model. Actually, we argue that the pervious cited works and others do not take in account the context of the geometries, and the use of 3D processing algorithms. Based on these observations, the idea behind this work is to benefit from the knowledge related to the scene structure and the different characteristics of geometries mainly to select the most suitable 3D processing algorithm from a 3D processing algorithm collection. In addition, in order to resolve the ambiguities issue of the scene caused by the sited constraints, more than one interaction between the semantic network and the 3D point clouds data is required.

In this paper, we claim that the domain of the semantic Web, and semantics technologies that it relies on, is of benefit for the definition of an automatic processing. One of the technologies is a language that helps to define ontologies; an evolved version of the semantic networks. Ontologies presents one of the most famous technology for knowledge modeling, where the basic ideas was to present information using graphs and logical structure to make computers able to understand and process it easily and automatically [12]. Our approach aims to structure knowledge, link geometrical objects to semantic information, create rules and finally guide the algorithms selection in 3D point clouds processing. The created knowledge will be structured in ontology. The produced ontology to orient the 3D object identification contain variety of data like the GIS data, images capture synchronized with the point clouds, information about the objects characteristics, the hierarchy of the sub elements, the geometrical topology, different processing algorithms etc. In the automatic process, the modeled knowledge will provide to the system relevant information aiming to orient the localization and the identification process. This purpose is reached by selecting the most suitable algorithm for the object detection and recognition. To achieve it, the ontology must contain information about objects characteristics like positions, geometrics information, images textures, etc. and also about the most suitable detection algorithms for each of existent objects.

III. SYSTEM OVERVIEW

As mentioned above, 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. If human knowledge could be inserted into automatic detection and reconstruction algorithms, point cloud processing would be more efficient and reliable. However, such a solution involves a lot of questions and challenges such as: (1) How can knowledge be structured based on heterogeneous sources? (2) How to create a coarse model suitable for different applications? (3) How to allow a dynamic interaction between the knowledge model and the 3D processing part?

In general, mathematical algorithms contain different data processing steps which are combined with internal decisions based on numerical results. This makes processing inflexible and error prone, especially when the data does not behave as the model behind the algorithm expects. We want to put these implicit decisions outside, make a semantic layer out of it and combine it with the object model. This approach is more flexible and can be easily extended, because knowledge and data processing are separated.

The created knowledge will serve to guide the numerical algorithms for 3D point cloud processing, based on rules that have been created and formalized before. The knowledge will be organized in an ontology structure. Knowledge not only describes the information of the objects, but also gives a framework for the control of the strategies selected. For instance, it provides rules for the localization and identification process. These rules guide the selection of individual algorithms or sequences allowing the detection and recognition of the object to be searched for. Once the knowledge provides initial information about the structure of the scene and the objects, candidate regions can be determined. Then, the algorithms integrated in the knowledge will be guided to identify objects. In other cases, when the existence of objects in the scene is ambiguous, we will search them in the point cloud based on updated information in the knowledge model. Consequently, knowledge-based methods will enable the algorithms to be executed reasonably and adaptively on particular situations. This is where WiDOP project will try to make a step forward.

IV. WIDOP PROCESSING CAPACITY

The WiDop project aims at the development of efficient and intelligent methods for an automated processing of terrestrial laser scanner data. Figure 2 presents the general coarse architecture for the WiDop project, composed of 3 parts: the knowledge part, the 3D processing part and the interaction management and control part labeled (WiDop Processing) ensuring the interaction between the above sited parts. In contrast to existing approaches, we aim at the utilization of previous knowledge on objects. This knowledge can be contained in databases, construction plans, as-built plans or Geographic Information Systems (GIS). Therefore, this knowledge is the basis for a selective, object-oriented detection, identification and, if necessary, modeling of the objects and elements of interest in the point cloud.

A. *The knowledge processing*

Our approach aims at structuring and modeling the existing knowledge in order to represent objects from the geometrical and the semantic point of view and to integrate important feature characteristics, if necessary. In the second step, this knowledge base will guide the numerical algorithms for 3D point cloud processing, based on rules that have been created and formalized before. This approach also follows the concept of Semantic Web, while the knowledge will be organized in an ontology structure, where the basic idea is to present information in a logical structure to make computers able to understand and process it easily and automatically.

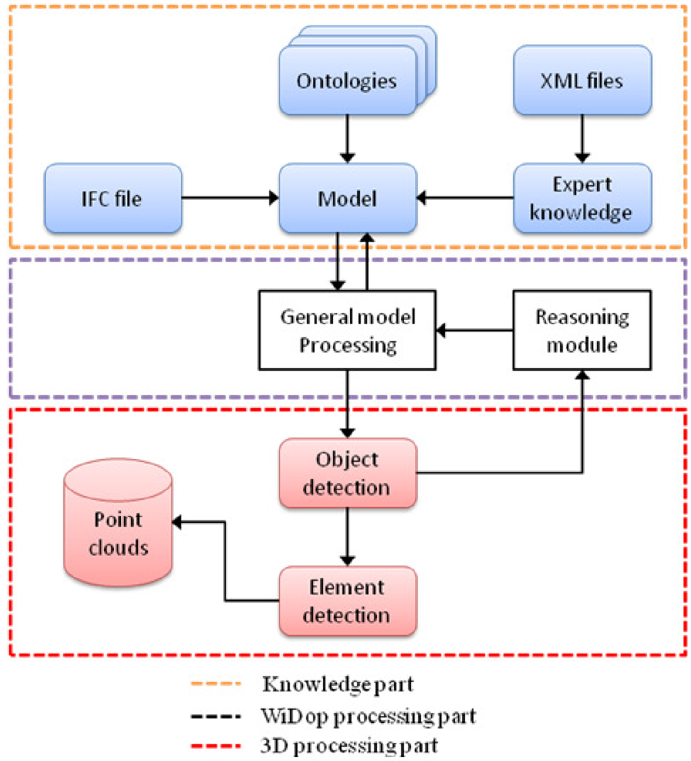

Figure 2. Overview system

Our approach is intended to use semantic knowledge based on OWL technology for knowledge modeling and processing. Knowledge has to be structured and formalized based on IFC schema, XML files, etc., using classes, instances, relations and rules. An object in the ontology can be modeled as presented; a room has elements composed of 4 walls, a ceiling and a floor. The sited elements are basic objects. They are defined by their geometry (plane, boundary, .), features (roughness, appearance, etc.), and also the qualified relations between them (adjacent wall, perpendicular, etc.). The object "room" gets its geometry from its elements and further characteristics may be added such as functions in order to estimate the existent sub elements. For instance a "classroom" will contain "tables", "chairs", "a blackboard", etc. The research of the object "room" will be based on an algorithmic strategy which will look for the different objects contained in the point cloud. This means, using different detection algorithms for each element, based on the above mentioned characteristics, will allow us to classify most of the point region in the different element categories. This prior knowledge is modeled in a Coarse Model (CM). It corresponds to the spatial structure of a building and it is an instance of semantic knowledge defined in the ontology. This instance defines the rough geometry and the semantics of the building elements without any real measurement. For example, a CM may define the number of stages, the type of roof, the configuration of the walls, the number of rooms per floor, the number of

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windows and doors per wall. In a CM, images and point clouds may be used as entry parameters for the process of data collection trying to correct the CM.

B. The 3D processing:

Numerical processing includes a number of algorithms or their combination to process the spatial data. Strategies include geometric elements detection (straight line, plane, surface, etc.), projection - based region estimation, histogram matrices, etc. All of these strategies are either under the guidance of knowledge, or use the previous knowledge to estimate the object intelligently and optimally. Alongside with 3D point clouds various types of input, data sets can be used such as images, range images, point clouds with intensity or color values, point clouds with individual images oriented to them or even stereo images without point cloud. All sources are exploited for application to particular strategies. Knowledge not only describes the information of the objects, but also gives a framework for the control of the selected strategies. The success rate of detection algorithms using RANSAC [21], Iterative Closest Point [22] and Least Squares Fitting [23] should significantly increase by making use of the knowledge background. However, we are planning not only to process point data sets but also based on a surface and volume representation like mesh and voxels, respectively. These methods will be selected in a flexible way, depending on the semantic context.

C. The WiDop processing:

In order to manage the interaction between the knowledge part and the 3D processing part, a new layer labeled the WiDop processing is created. This layer ensures the control and the management of the information transaction and the decision taken, based on several steps, as outlined in Figure 3. The steps are:

- The algorithmic strategy selection.
- The update of the *Coarse Model*.
- The topological search of new objects.
- The semantic characterization of new objects.

In the next section, the mixed strategy based on the WiDop processing layer is presented in detail in order to show the different interactions that takes place during the WiDop reconstruction process between the knowledge base and the 3D processing algorithms.

V. THE INTERACTION MANAGMENT

We propose a mixed strategy based on WiDop processing layer insuring the interaction between the knowledge base and the 3D processing algorithms (Figure 2). It presents an intermediary between the semantic based strategy and the 3D processing one. In this section, the global view of our mixed strategy will be presented and the ultimate interaction between both of parts is described.

As seen in Figure 3, the mixed strategy is based on two principles axes which are the geometric resolution based on the 3D processing domain and the semantic one based on the semantic web technology.

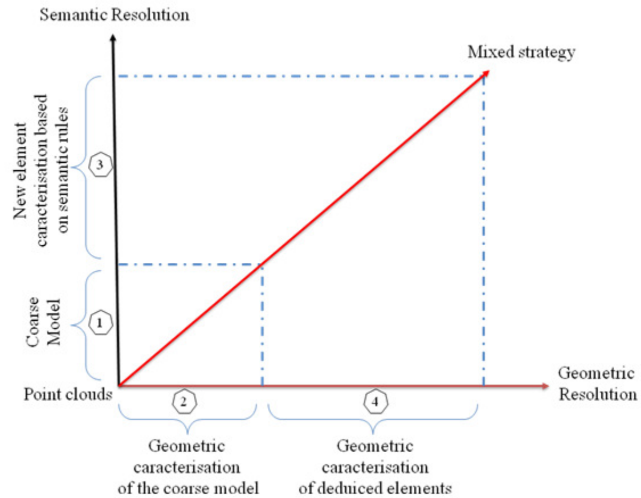

Figure 3. The mixed strategy, a system overview.

Such strategy can be divided in two main steps: The first step is the geometric quantification, detection and recognition of the different existent objects in the coarse model. In this phase, the purpose of the processing is the detection of the defined objects in the coarse model. This is ensured by linking the high level semantic object definition in the coarse model and the correspondent portion of the point clouds. The second one aims at the semantic characterization of new objects in point clouds is based on the topologic relations. The inference will be based on the "Coarse model" CM and on the detected and localized objects. In this step, based on the relation´s interpretation and the interference rules management, new objects in the point cloud will be inferred and detected automatically (Figure 3).

In order to focus on our method for the combination of the semantic web technology and the 3D processing algorithms, Figure 4 illustrates an UML sequence diagram that represents the general design of the proposed solution. Hence, the purpose is to create a more flexible, easily extended approach where algorithms will be executed reasonably and adaptively on particular situations. The system architecture is divided into four actors: the data base, the 3D processing, the WiDop processing and the knowledge base.

To simplify the illustration, we will use a single data set type. In fact, we are limited in working on point clouds generated by a laser scanner. This does not mean that we will not profit from others resources like images, panoramic images, videos, etc. For this reason, the mentioned source presenting the fourth actor in the diagram is a laser scanner providing millions of point clouds. For the rest of the section, the real mechanism related to our solution will be disambiguated in details beginning by how our ontology is created, how knowledge are linked to the 3D processing algorithms arriving to how objects are detected and semantic model is updated.

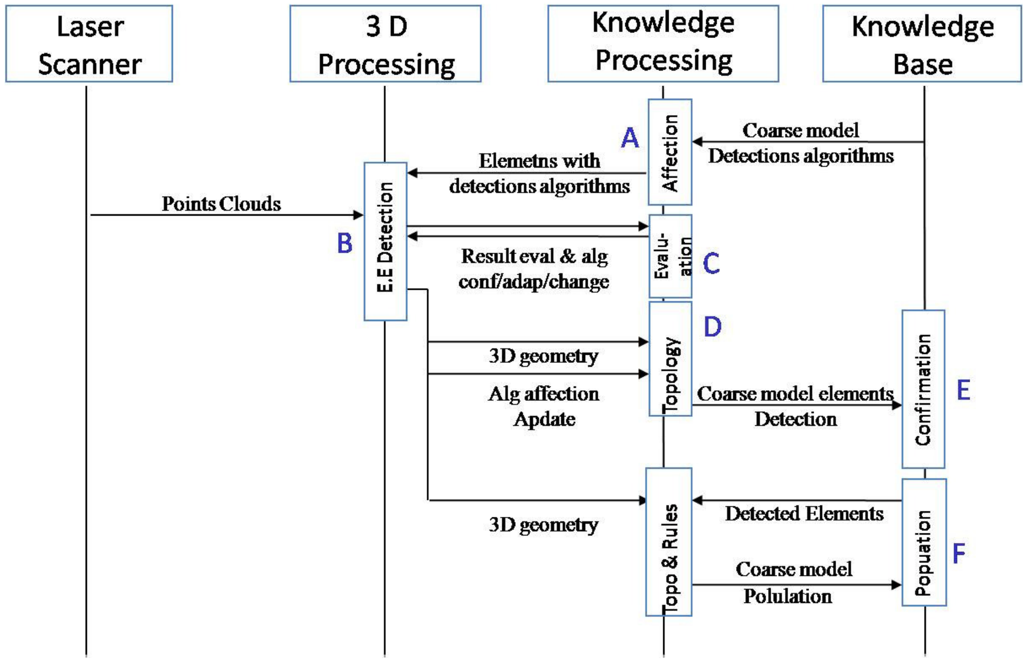

Figure 4. The sequence diagram of interactions between the laser scanner, the 3D processing,the knwoldege processing and the knowledge base.

A. *The Ontology Creation*

The WiDop project deals with the creation of an ontology corresponding to the project requirements. In this field, two different strategies for the ontology creation can be used. In the first one, the ontology is created manually depending on our vision and on the business knowledge provided by the specialists of the domain. Such ontology will look like a bottom up ontology [13], [14], very precise and designed for a specific domain. In the second one, it can be automatically generated based on different sources like ontologies from different domains such as the transport, the railway and the geometric ones [15]. The generation of the ontology can be also done based on software's packages thanks to many tools like the XML2OWL [17], [19]. It serves to map XML files provided from Metronome Db Clear Suite software used for the management of the Deutsche Bahn point cloud´s, allowing a manual tagging of the different selected elements and describing the general structure for the railway domain to an OWL file. It can also be ensured by the IFC/XML tools mapping IFC files for the building management structure to OWL one. From our point of view, the WiDop ontology must respect the applied areas specification (railway or Fraport). Based on this observation, our ontology is created automatically in order to have a general model then adapted manually to respect the real scene characteristics. The schema extracted from the XML data base provided from the DB Clear suite software, will be exploited to facilitate the automatic population of our ontology. Once our knowledge base is created and populated, it will be used as an entry for the WiDop project (Figure 5).

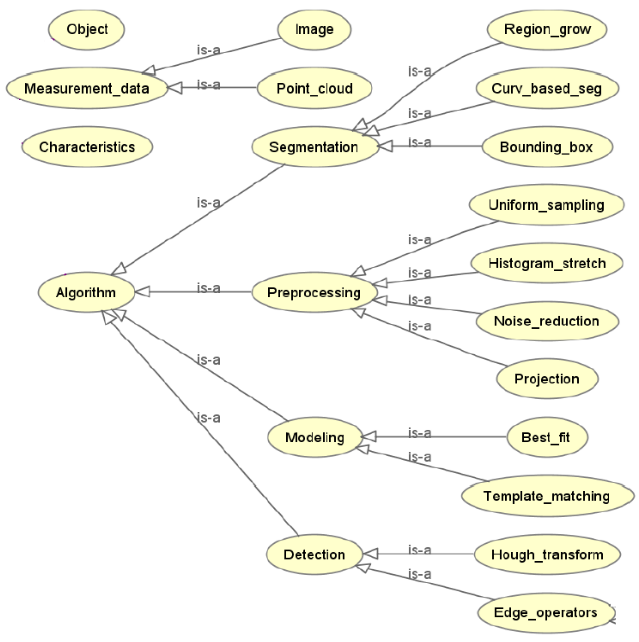

Figure 5. Portion of the developped ontology describing the "Algorithm" class

B. *Integrating Knowledge in 3D object detection*

The proposed approach couples the semantic web technology represented by the knowledge to the 3D processing one represented by the 3D processing algorithms. Let's remember that the idea behind this project is to direct, adapt and select the most suitable algorithms based on the

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objects characteristics. In fact, one algorithm could not detect and recognize different existent objects in the 3D point clouds, since they are distinguished by different shapes, size and capture condition. The role of knowledge is to provide not only the object's characteristics (shape, size, color, etc.) but also object's status (visibility, correlation) to algorithmic part, in order to adjust its parameters to adapt with current situation, Table 1. Based on theses observation, we draw links from algorithms to objects based on the similar characteristics, as Figure 6 shows.

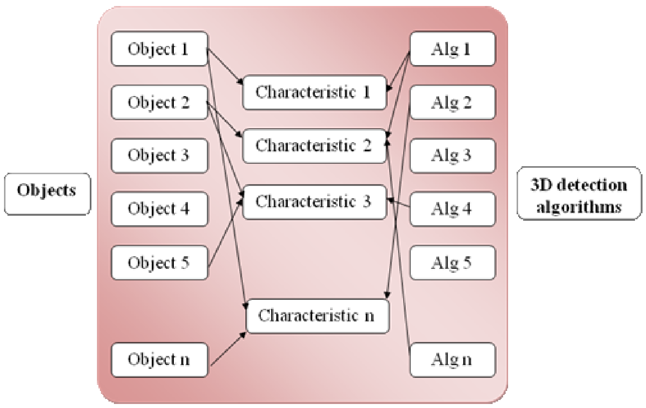

Figure 6. Linking algorithms and objects.

The knowledge part controls one or more algorithms for the detection of objects. In order to carry out this detection, we benefit from the experience of experts in 3D processing. This experience helps to find a match between the object’s characteristics and the algorithm’s characteristics. Actually, a certain algorithm can be used for the detection of a certain object in a certain context. The set of characteristics are determined by the object’s properties such as geometrical features and appearance. Then, the role of the knowledge is also to provide the algorithms that can detect and recognize these characteristics. These characteristics are considered as values and it can change the parameters of the algorithms. After the detection of an object, there is a module that gives a feedback about the status of the detected object according to the knowledge part and in order to adjust the algorithms to improve the robustness. Due to these frequent updates, the combination of knowledge and the 3D processing becomes relevant and flexible, c.f. Table1.

TABLE 1. THE CHARACTERISTICS LIST OF ALGORITHM'S AND OBJECT'S INPUT

No	*Characteristics*
1	Geometry (plane, sphere, arc)
2	Corner
3	2D boundary
4	Size
5	Orientation
6	Appearance (colour, surface material)
7	Visibility
8	Correlative position

C. The Geometry Processing

The third part in this model is the digital treatments. This part will focus on the object detection based on the prior knowledge and the selected algorithm. As seen in Figure 4, once the algorithms are affected, the 3D processing layer will provide the generated point clouds from the laser scanners, it will also be provided with the different pieces of information relative to each object in the ontology. The 3D layer must have as information:

- The object label
- The object location coordinate
- The object spatial coordinate
- The eventual 3D shape of the object
- The sub-elements composing the object
- The object complexity rate
- The most suitable detection algorithm to use
- …….

Depending on the object complexity, there are two possible scenarios. In the case of a low complexity rate, the objects can be detected automatically based on a template matching algorithm [20]. Else, the objects will be decomposed into elementary sub-objects as shown in the area B of Figure 4. Once detected, an evaluation process will estimate the detection quality rate (Figure 4, area C), and a topological reconstruction of the root element will be executed (Figure 4, area D). Once the coarse model elements are detected and recognized, (Figure 4, area E), the semantic research of new objects step is stimulated.

D. The Semantic Qualification

The described technique for the geometric qualification of the coarse model above aims at the detection of the maximum existing elements in the CM. Normally, a real scene should always contain extra object or unexpected one. To ensure a high detection quality rate, we suggest a second main module for our strategy aiming to identify new object in the coarse model. In fact, knowledge contains a reasoning capacity able to infer logical consequences from a set of asserted facts. Our model will be able to infer new objects and relations based on the coarse model topological relation and on the detected and identified elements (Figure 4, area F).

VI. CONCLUSION AND FUTURE WORK

The proposed approach for 3D object recognition in point clouds labeled "Mixed Strategy" present our initial work and vision on the project. It aims to improve the object localization and the scene reconstruction leading to a more robust and efficient processing of 3D point clouds and image data since it is based on interaction between two complementary domains, the semantic web and the 3D processing one via an intermediary layer labeled WiDop processing.

The integration of knowledge into 3D processing is a promising solution. It could make the object detection algorithms more robust, flexible and adaptive in the different circumstances through the knowledge guidance via a new mechanism under construction named "3D processing rules". Such mechanism aims to connect ontology to 3d processing algorithm via new Built-Ins. Once executed, these rules will query the ontology and the point clouds via the activation and the instantiation of the most suitable 3D processing algorithm.

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REFERENCES

[1] Vanlande, R., Nicolle, C., and Cruz, C. 2008. “IFC and building lifecycle management,” Elsevier, Automation in Construction, Vol. 18, pp. 70-78.

[2] Zitova, B., and Flusser, J. 2003. “Image registration methods: a survey,” Elsevier, Image and vision computing. Vol. 21, pp. 977-1000.

[3] Vosselman, G., and Dijkman, S. 2001. “3D building model reconstruction from point clouds and ground plans,” International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences, Vol. 34, pp. 37-44.

[4] Pollefeys, M. 2000. “Automated reconstruction of 3D scenes from sequences of images,” Elsevier, ISPRS Journal Of Photogrammetry And Remote Sensing, Vol. 55, pp. 251-267.

[5] Hartley, R., and Zisserman, A. 2003. “Multiple view geometry in computer vision,” Cambridge University Press New York, NY, USA.

[6] Brunn, A. 2000. “A step towards semantic-based building reconstruction using markov-random-fields,” INTERNATIONAL ARCHIVES OF PHOTOGRAMMETRY AND REMOTE SENSING, v 33, pp. 117-124.

[7] Scholze, S. Moons, T., and Van Gool, L. 2002. “A probabilistic approach to building roof reconstruction using semantic labelling,” Pattern Recognition. pp. 257-264.

[8] Grimson, W E. 1986. “From images to surfaces: A computational study of the human early visual system,” MIT press Cambridge, Massachusetts.

[9] Cantzler, H. Fisher, R., and Devy, M. 2002. “Quality enhancement of reconstructed 3D models using coplanarity and constraints,” Springer, Pattern Recognition, pp. 34-41.

[10] Nuchter, A., Surmann, H., and Hertzberg, J. 2003. “Automatic model refinement for 3D reconstruction with mobile robots,” IEEE Computer Society, pp. 394-401.

[11] Grau, O. 1997. “A scene analysis system for the generation of 3-D models,” First International Conference on Recent Advances in 3-D Digital Imaging and Modeling (3DIM '97) pp. 221.

[12] Borst, WN., Akkermans, JM., and Top, JL. 1997. “Engineering ontologies,” International Journal of Human-Computer Studies, Vol. 46, pp. 365-406.

[13] Van der Vet, PE., and Mars, NJI. 1998. “Bottom-up construction of ontologies,” IEEE Transactions on Knowledge and data Engineering, Vol. 10, pp. 513-526.

[14] Hare, JS., Sinclair, P. A. S., Lewis, P. H., Martinez, K., Enser, P. G. B., and Sandom, C. J. 2006. “Bridging the Semantic Gap in Multimedia Information Retrieval: Top-down and Bottom-up approaches,” Mastering the Gap: From Information Extraction to Semantic Representation / 3rd European Semantic Web Conference, 12 June 2006, Budva, Montenegro.

[15] Stumme, G., and Maedche, A . 2001. “Ontology merging for federated ontologies on the semantic web,” Proceedings of the International Workshop for Foundations of Models for Information Integration (FMII-2001), pp. 413-418.

[16] Dista: http://www.i3mainz.fh-mainz.de/Article68.html. The last access date: 04-08-2010.

[17] Bohring, H., and Auer S. 2005. “Mapping XML to OWL ontologies,” Leipziger Informatik-Tage, Vol. 72 of LNI, GI, pp.147-156.

[18] Leica®: http://www.leica-geosystems.fr/fr/index.htm. The last access date: 04-08-2010.

[19] Cruz, C., and Nicolle, C. 2008. “Ontology Enrichment and Automatic Population From XML Data,” ODBIS. pp.17-20.

[20] Kenue, S.K. “LANELOK: Detection of lane boundaries and vehicle tracking using image-processing techniques- part II: Template matching algorithms,” SPIE Conference on Mobile Robots. pp. 234-245.

[21] Lacey, AJ., Pinitkarn, N., and Thacker, N.A. “Faithful least-squares fitting of spheres, cylinders, cones and tori for reliable segmentation,” Proceedings of the British Machine Vision Conference (BMVC) 2000.

[22] Besl, P.J., and McKay, N.D. 1992. “A Method for Registration of 3-D Shapes,” IEEE Trans. Pattern Analysis and Machine Intelligence, V 14, pp. 239-256.

[23] Arun, KS., Huang, T.S., and Blostein, S.D. “Least-squares fitting of two 3-D point sets,” IEEE TRANS. PATTERN ANAL, MACH. INTELLIG 1987. pp. 698-700.

[24] Marbs, A., Boochs, F., Ben Hmida, H., and Truong, H. 2010. “Wissensbasierte Objekterkennung in 3D-Punktwolken und Bildern,” DGPF-Tagungsband, 3-Ländertagung D-A-CH Conference Wien, pp. 220-227.

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