

# INTEGRATION OF KNOWLEDGE INTO THE DETECTION OF OBJECTS IN POINT CLOUDS

H. Q. Truong<sup>\*</sup>, H. B. Hmida, A. Marbs, F. Boochs

i3mainz, Mainz University of Applied Sciences, Lucy-Hillebrand Str. 2, 55128 Mainz, Germany -  
(hung.truong, helmi.benhmida, andreas.marbs, boochs)@geoinform.fh-mainz.de

Commission III, WG III/2

**KEY WORDS:** Laser scanning, knowledge base, point clouds, processing, recognition

## ABSTRACT:

The reconstruction of 3D objects from point clouds and images is a major task in many application fields. The processing of such spatial data, especially 3D point clouds from terrestrial laser scanners, generally consumes time and requires extensive interaction between a human and the machine to yield a promising result. Presently, algorithms for an automatic processing are usually data-driven and concentrate on geometric feature extraction. 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 modelled by purely numerical strategies. Therefore, the intention of our approach is to take human cognitive strategy as an example, and to simulate these processes based on available knowledge for the objects of interest. Such processes will first, introduce a semantic structure for the objects and second, guide the algorithms used to detect and recognize objects, which will yield a higher effectiveness. Hence, our research proposes an approach using knowledge to guide the algorithms in 3D point cloud and image processing.

## 1. INTRODUCTION / MOTIVATION

In the past decade terrestrial laser scanners have been established as a workhorse for topographic and building survey. With every new scanner model on the market, phase-shift scanners in particular, the instruments become faster, more accurate and can scan objects at longer distances. Laser scanners tests, which have been carried out at our institution for eight years now, prove this observation (Böhler, Marbs, 2010). However, increasing scanning speed leads to a new behaviour of the user in the field. While scan region and resolution have to be chosen carefully using slower pulse scanners, with phase-shift scanners usually complete scans with high resolution are carried out, accepting a huge redundancy concerning the number and density of the points. This leads to a shift of the amount of work from the field to the office. Depending on the task, the field time / office time ratio can be between 1:5 and 1:30, because in most cases, processing techniques are still mainly affected by manual interaction of the user. Typical operations are cleaning of the point cloud, deleting unnecessary areas, navigation in an often huge and complicated 3D structure, selection of sets of points, extraction and modelling of geometries and objects. At the same time it would be much more effective, to process the data automatically, which has already been recorded in a very fast and effective way.

The development of algorithms for the (semi-)automatic post-processing of laser scanner point clouds has been a research issue for even more than 10 years now, thanks to the airborne laser scanning. Exemplarily the work of TU Delft (Pu, Vosselman, 2006) and TU Dresden (Hofman et al., 2003) shall be mentioned. All those algorithms are mainly data-driven, utilizing techniques like region-growing, projections, morphological operators, line-detection, 3D Hough transformation or parameter space analysis. Those algorithmic strategies have been adapted to the respective objects, which should be detected and modelled in the point cloud, for instance roof types or building facades. These strategies have one thing

in common: they are static and do not allow a dynamic adjustment to the object or to initial processing results. The algorithm to use will be applied to the whole point cloud and the result can be good or bad, depending on several parameters like point cloud quality, object distribution, object features and so on. But, there is no feedback to the algorithmic part in order to activate a different algorithm or just the same algorithm with changed parameters. This interaction is still up to the user who has to decide by himself, which algorithms to apply for which kind of objects and point clouds, which again leads to a time-consuming, mostly manual process. This is where our project will try to make a step forward. The goal is to develop efficient and intelligent methods for an automated processing of terrestrial laser scanner data. In addition, other data sources like images, stereo pairs or point cloud colour information shall also be included in the detection process. In contrast to existing approaches, we aim at utilizing previous knowledge on the objects to measure. This knowledge can be contained in databases, construction plans, as-built plans, Geographic Information Systems (GIS) or just in the heads of the domain experts and therefore is the basis for a selective, object-oriented detection, identification and, if necessary, modelling of the objects and elements of interest in the point clouds.

It is intended to use semantic based on Ontology Web Language (OWL) for knowledge modelling and processing. The previous knowledge has to be structured and formalized, using classes, instances, relations and rules. Guided by the knowledge base, a tool named "WiDOP processing" will control the selection and parameterization of numeric algorithms for point cloud and image processing. Based on the processing results, a feedback will be given to the knowledge base and the WiDOP processing respectively in order to decide, whether the object detection was successful and, when necessary, activate an adapted numeric processing.

## 2. RELATED WORK

The reconstruction of 3D scene has occupied a wide area of computer vision. In most cases such reconstruction is based on 3D processing algorithms extracted from the signal processing domain. Recent work aims to reconstruct scenes based on semantic networks describing the relation between the scene objects. Based on these observations, the following section will be articulated in two parts: the first one will present reconstruction methods based on signal processing algorithms while the second one will describe methods based on semantic networks technology.

### 2.1 3D processing methods

Within the Terrestrial Laser Scanning (TLS) processing methods might be separated into three different classes, which will be explained in the following. One class presents reconstruction methods based on manual processing of 3D point clouds. A second one explains semi-automatic methods assisted by human, while a third class focuses on automatic methods.

**Manual methods:** They 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 packages.

**Semi-automatic methods:** Concerning the semi-automatic 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 element projection, affine, and Euclidean geometries (Zitova and Flusser, 2003) for the definition of constraints. When modelling buildings by constructive solid geometry, buildings can be regarded as compositions of a few components with simple roof shapes, like flat roofs, gable roofs and hip roofs (Vosselman and Dijkman, 2001). Vosselman 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 intersecting lines and height jump edges between planar faces. Once done, the component composition is made manually.

**Automatic methods:** Automatic methods use various approaches but all are based on segmentation techniques to extract features. The methods of (Pollefeys, Koch, Vergauwen and Van Gool, 2000) and (Hartley and Zisserman, 2003) use the projective geometry technique. Pollefeys method divides the task of 3D modelling into several steps. The system combines various algorithms from computer vision, like projective reconstruction, auto-calibration and depth map estimation. The approach of A. Zisserman proceeds in two steps. First, a coarse surface model of the building is defined. 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.

### 2.2 Knowledge based methods

All the above strategies are based on signal processing algorithms, but, other strategies also exist. They are based on semantic networks to guide the reconstruction like the project

Aida (Weik and Grau, 1996). The knowledge part in Aida is modelled with a semantic network forming. A semantic network is a network that represents semantic relations among a concept; it is a directed or an undirected graph consisting of vertices which represent concepts and edges (Sowa and Borgida, 1991). To describe the objects and their relations, an independent language is defined. This language is inspired by the network syntax of ERNEST (Niemann, 1990). During the phase of interpretation, a semantic value is assigned to each geometric primitive resulting in the semantic network. This network is an instance of the model. At the end, when all primitives are labelled, the assigned semantics is correct.

Our approach aims to structure knowledge, to link geometrical objects to semantic information, to create rules and finally to guide the algorithms selection in 3D point clouds processing. This concept was first introduced in (Boochs, 2009) and will be explained more detailed in this paper. As shown in the previous paragraph, the semantic network is good for representing the upper-class/subclass relationships and it is useful for representing instances for each class. But, concerning restrictions on relationships and characteristics, such technology will fail. Instead, based on Ontology Web Language, it is possible to specify object characteristics, which provides a powerful mechanism for enhanced reasoning about transitive, symmetric, functional properties and others. Based on these observations, the created knowledge will be structured in an ontology. In an automatic process, the modelled knowledge will provide relevant information aiming to control the localization and the identification process. This purpose is reached by selecting the most effective algorithmic strategy for the object detection and recognition. To achieve it, amongst others the ontology must contain information about objects characteristics like positions, geometrics information, images textures and also about the most suitable detection algorithms for each of the existent objects and geometries.

## 3. 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, 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.

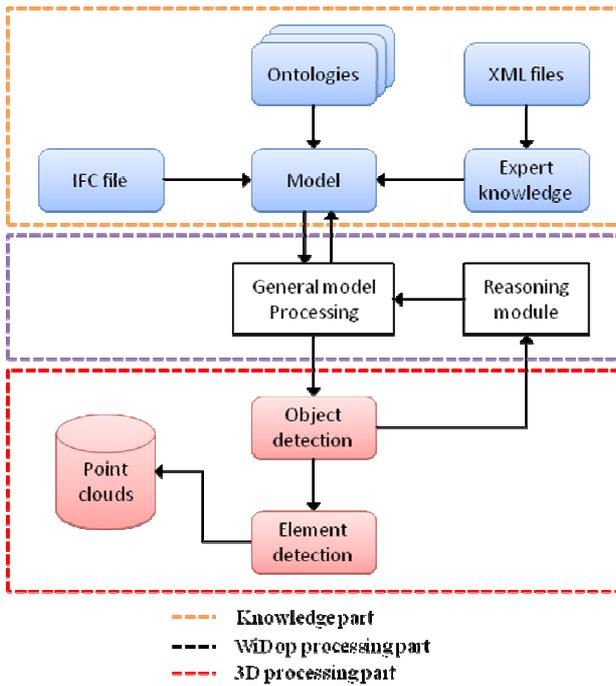


Figure 1. Overview system

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. It can be based on a variety of knowledge/data sources like GIS data, CAD drawings, databases, building information models or just plain xml or text files, describing some characteristics or relations of the objects to detect. 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 thereof allowing the detection and recognition of the object to be searched for.

Numerical processing includes a number of algorithms or the combination of them to process the data. The various types of input data sets can be used such as 3D point clouds, images, range images, point clouds with intensity or colour values, point clouds with individual images oriented to them or even stereo images without point cloud. The algorithms are grouped following a proposed structure which will be explained in section 5. This classification makes the guidance and selection of knowledge faster and easier. The success rate of detection algorithms using RANSAC, Iterative Closest Point and Least Squares Fitting 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. 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.

#### 4. KNOWLEDGE MODELLING

Our approach aims to structure and integrate knowledge about objects and numerical algorithms for the 3D data processing. It follows the concept of Semantic Web while the knowledge will be organized in an ontology structure. Ontologies present one of the most famous technologies for knowledge modelling where the basic idea is to present information in a logical structure to make computers able to understand and process it easily and automatically. Ontology definition was originally proposed in 1993 by Tom Gruber, as “an explicit specification of a conceptualization” (Gruber, 1993) defining the “basic terms and relations comprising the vocabulary of a topic area, as well as the rules for combining terms and relations to define extensions to the vocabulary” (Giarretta, 1995).

Our WiDOP project deals with the creation of an ontology corresponding to the project requirement. To achieve this, the ontology must provide information about object characteristics like position and orientation, size and shape, surface and colour, proximity relationships and many more. Eventually, the model must contain information about the most suitable algorithms for the detection, identification and, if necessary, reconstruction of the objects. In the end, this approach will lead to a more reliable, efficient automated object detection, using artificial intelligence instead of human interaction.

In this field, two different strategies for the ontology creation can be distinguished. The first, more specific one, creates ontologies based on an individual vision and on the business knowledge provided by the specialists of the domain. Such ontology will look like a bottom up ontology (Van der Vet, 1998, Hare, 2006), very precise and designed for a specific domain. The second, more general one, generates ontologies automatically based on existing sources like domain ontologies which exist for areas like transport or railway systems (Euzenat, 2004). The generation of the ontology can also be done based on software tools like the XML2OWL (Bohring and Auer, 2005). It can also be ensured by the IFC/XML tools mapping IFC files for the building management structure to OWL structure. It can also be based on a variety of other knowledge/data sources like GIS data, CAD drawings, database, building information models, describing some characteristics or relations of the objects to detect.

From our point of view, WiDOP ontology must have a high rate of abstractness, although this, it must respect the applied domain specifications (railway or fraport). Based on these observations, our ontology is created as a general model first, and then adapted manually to respect the real scene characteristics. Once our knowledge base is created and populated, it will be used as an entry for the WiDOP project, Figure 2. To clarify how a concept can be described in an ontology, an object for example can be modelled as presented; a room has elements like 4 walls, a ceiling and a floor. The cited elements are basic objects. They are defined by their geometry (plane, boundary...), features (like roughness, appearance...), and also the qualified relations between them (adjacent wall, perpendicular...). The object “room” gets its geometry from its elements and further characteristics may be added like functions in order to estimate the existent sub elements e.g. “classroom” will contain “tables”, “chairs”, “blackboard”, etc.

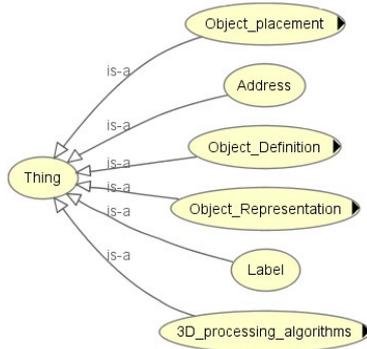


Figure 2. A branch of WiDOP ontology

This prior knowledge is modelled 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 windows and doors per wall.

## 5. INTEGRATING KNOWLEDGE IN 3D OBJECT DETECTION

### 5.1 The structure of algorithms

In this section, we will discuss the algorithms of 3D object detection in point clouds and images. Each particular algorithm will correspond to individual data characteristics. Those characteristics can be based on geometric or on radiometric information. Therefore both point clouds and images can be used as input data. With a large variety of different object types of diverse complexity we need a collection of many algorithms. In order to manage them, we propose to classify them into individual groups. This is to structure the "toolbox" in order to make the algorithms available for easy access under the guidance of knowledge. An example for a possible classification is shown in table 1.

No	Group
1	Noise reduction / Cleaning
2	Resolution reduction
3	Segmentation
4	Detection
5	Recognition
6	Reconstruction / Representation

Table 1. Algorithm classification

Basically, there are 6 main groups to classify algorithms based on their function. For example, group 1 "noise reduction / cleaning" and group 2 "Resolution reduction" specialises in data processing. Group 1 is to reduce the useless information in both images and point clouds, while group 2 tends to reduce the weight of data, such as the number of points high density areas. Group 3 "Segmentation" is usually used for separating the regions of data based on certain features, then the next algorithms will execute in segmented area. Group 4 "Detection" and 5 "Recognition" contains the main algorithms that will be used to detect and recognise the objects based on knowledge. Group 6 "Reconstruction / Representation" contains methods which can recognise objects or geometries after the raw data has

been transformed to a different representation (e.g. triangular mesh or histograms for point cloud data).

Here, we mention some significant algorithms which have been proposed:

#### Group 1: Noise reduction

**Image enhancement:** Here is a set of algorithms which process the colour images, such as: noise reduction, thinning lines, morphologies, sharp edge boundaries and so on.

**Point clouds noise reduction:** In order to restrict the error in the algorithms processing on point clouds, we consider a method which can reduce the noise caused by a lited scanner accuracy. This is especially effective to fitting algorithms based on approximate estimation.

#### Group 2: Resolution reduction

**Uniform resolution reduction:** A simple method aims to reduce the number of points equally in the whole point cloud.

**Adaptive resolution reduction:** Sometimes it is more effective and optimal to keep the points only in the interest region, while thinning the point density in the other parts.

#### Group 3: Segmentation

**Colour based segmentation:** When object's colour is different from background and among others, it is easy to detect it, just only using this colour information. First, we define the object's colour, then analyse the colour of background as segmenting them into certain different colour groups (Chen et al., 2008). Depending on the complex texture of background, we can choose the number of colour groups. Finally, we match between the object's colours with the particular region of background after segmentation, in order to locate where the object position can probably be.

**Bounding box:** Through knowledge base, we predict relatively the position of objects in point clouds. Then, each approximate position will be assigned and represented by a bounding box, all based on the size and central coordinate approximation of interesting objects.

#### Group 4, 5: Detection and Recognition

**Plane fitting using least squares:** First the point cloud data is divided in small "cubes" with specific dimension. By this, we can process the data in each cube and omit the empty one, this is to optimize the processing time. After that, we apply least square fitting to detect plane individually, then combine them together becoming a big one. This can also be applied for line detection.

**Region growing:** This algorithm utilises for detecting the regions which have the same property, such as region of coplanar points or sets of points which belong to the same curved surface, like sphere or cylinder.

**Eigen values estimation to gain object structures:** All points in a spherical cell will be analyzed. Then, the concept of structure tensors is applied to find features of each point through eigen-decomposition (Gross and Thoennessen, 2006). The feature here means the coherence of this point with neighbourhoods. Finally, we classify the geometrical structures

such as isolated point, line, plane etc. based on the values of eigenvalues and eigenvectors.

### Group 6: Reconstruction / Representation

**Combination of density and height histogram:** In this approach, we rely upon the idea of recognizing the object structure based on density histogram (accumulation of points following vertical direction) and height histogram (z values matrix). Each parts of object will be reconstructed following vertical direction (Nir, 2006). This method is good for structures like buildings or urban scenes.

**Triangulation representation:** We represent the surface from point cloud as a triangular mesh. Then, we examine the orientation of each triangle and group them based on its normal vector's direction. Finally, we have some bigger plane following the direction which we want to search.

These algorithms are just a small sample of the whole toolbox or catalogue of algorithms we plan to use. Many more will be analysed, modelled in the knowledge base and used for object detection.

### 5.2 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 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, colour...) but also object's status (visibility, correlation) to algorithmic part, in order to adjust its parameters to adapt with current situation.

Based on these observation, we issue a link from algorithms to objects based on the similar characteristics, as Figure 3 shows.

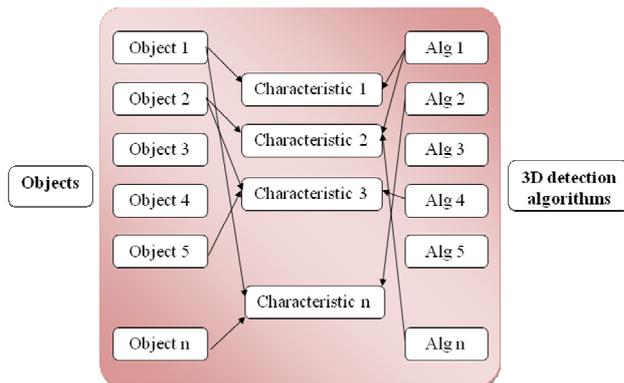


Figure 3. Algorithms selection based on object's characteristics

Knowledge part controls one or more algorithms for detecting object. To do this, we try to find a match between the object's characteristics and the characteristics, a certain algorithm can be used for . For example, object O has characteristics: C<sub>1</sub>, C<sub>2</sub>, C<sub>3</sub>; and algorithm A<sub>i</sub> can detect characteristic C<sub>1</sub>, C<sub>3</sub>, C<sub>4</sub>, while algorithm A<sub>j</sub> can detect characteristic C<sub>2</sub>, C<sub>5</sub>. Then, decision algorithm will select A<sub>i</sub> and A<sub>j</sub> since these algorithms have capability detecting the characteristics of object O. The set of

characteristics are determined by the object's properties such as geometrical features and appearance. Then, the role of the 3D processing part is to provide the algorithms that can detect and recognise these characteristics.

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

Table 2. The characteristics list of algorithm's and object's input

Furthermore, we have the visibility and correlative position of an object. These characteristics are considered as values can change the parameters of algorithms adapting with current conditions. After an object is detected, there is a module to feedback the status of object to knowledge part and to adjust for algorithms in order to make them more robust. Due to this frequent update, the combination of knowledge and 3D processing part becomes intelligent and flexible.

## 6. CONCLUSION AND FUTURE WORK

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. However, in order to solve the individual scenes, we need to create their own ontology. Therefore it requires new strategies in both knowledge and 3D processing to deal with all general cases. For the future work we focus on improving some modules such as decision logic and reasoning capacity of ontology structure. In the meantime, finding and using new 3D processing algorithms is another task.

## ACKNOWLEDGEMENT

The work presented in this paper is part of the research project WiDOP – Wissensbasierte Detektion von Objekten in Punktwolken für Anwendungen im Ingenieurbereich, funded by the German Federal Ministry for Research and Education (grant no. 1758X09). Partners in the project are Metronom Automation GmbH and DB Netz AG (for the railway domain) and Fraport AG (for the facility management domain). The project started in October 2009 and will be finished in September 2012.

## REFERENCES

- Böhler, W. and Marbs, A., 2010. Investigating Laser Scanner Accuracy. <http://scanning.fh-mainz.de/scannertest/results/300305.pdf> (accessed 21 May 2010)
- Bohring, H and Auer, S., 2005. Mapping xml to owl ontologies. In: *Leipziger Informatik-Tage*, Vol. 72, pp. 147-156.
- Boochs, F., Kern, F., Marbs, A., Schütze, R., 2009. Ansätze zur geometrischen und semantischen Modellierung von großen, unstrukturierten 3D-Punktmengen. In: *DGPF Tagungsband 18*, Jena, Germany.

- Chen, T.W., Chen, Y.L. and Chien, S.Y., 2008. Fast image segmentation based on K-Means clustering with histograms in HSV color space. In: *2008 IEEE 10th Workshop on Multimedia Signal Processing*, Queensland, Australia, pp. 322-325.
- Euzenat, J., 2004. An API for ontology alignment, 2004. In: *The Semantic Web-ISWC*, pp. 698-712.
- Giaretta, P., Ontologies and Knowledge Bases Towards a Terminological Clarification, 1995. In: *Towards very large knowledge bases: knowledge building & knowledge sharing*, 1995, p. 25.
- Gross, H., Thoennessen, U. and Publica, F., 2006. Extraction of Lines from Laser Point Clouds. In: *Symposium of ISPRS Commission III: Photogrammetric Computer Vision PCV06. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Bonn, Germany, Vol. 36, pp. 86-91.
- Gruber, T.R., A translation approach to portable ontology specifications, 1993. In: *Knowledge acquisition*, Vol. 5, pp. 199.
- Niemann, H., Sagerer, G. and Schröder, S., 1990. ERNEST: A Semantic Network System for Pattern Understanding. In: *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 12, No. 9, pp. 883-905.
- Hare, J. S., 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. In: *Mastering the Gap: From Information Extraction to Semantic Representation / 3rd European Semantic Web Conference*, Budva, Montenegro.
- Hartley, R and Zisserman, A., 2003. *Multiple view geometry in computer vision*. Cambridge Univ Pr.
- Hofmann, A.D., Maas, H.G. and Streilein, A., 2003. Derivation of roof types by cluster analysis in parameter spaces of airborne laserscanner point clouds. In: *International Archives of Photogrammetry and Remote Sensing*, Dresden, Germany, Vol. 34, Part 3/W13, pp. 112-117.
- Nir, E., 2006. Using Histogram Matrices as an Interface for Designing with Parametric Point-Clouds. In: *Communicating Space (s) 24th eCAADe Conference Proceedings*, Volos, Greece, pp. 764-769.
- Pollefeys, M., Koch, R., Vergauwen, M. and Van Gool, L., 2000. Automated reconstruction of 3D scenes from sequences of images. In: *ISPRS Journal Of Photogrammetry And Remote Sensing*, Vol. 55, No. 4, pp. 251-267.
- Pu, S. and Vosselman, G., 2006.: Automatic extraction of building features from terrestrial laser scanning. In: *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Dresden, Germany, Vol. 36, Part 5, pp. 25-27.
- Sowa, J.F. and Borgida, A., 1991. *Principles of Semantic Networks: Explorations in the representation of knowledge*. Morgan Kaufmann, San Mateo, CA, USA.
- Van der Vet, PE. and Mars, NJI., 1998. Bottom-up construction of ontologies. In: *IEEE Transactions on Knowledge and data Engineering*, Vol. 10, No. 4, pp. 513-526.
- Vosselman, G and Dijkman, S., 2001. 3D building model reconstruction from point clouds and ground plans. In: *International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences*, Athens, Georgia, USA, Vol. 34, pp. 37-44.
- Weik, S and Grau, O., 1996. Recovering 3-D object geometry using a generic constraint description. In: *International Archives of Photogrammetry and Remote Sensing*, Vol. 31, pp. 593-598.
- Zitova, B and Flusser, J., 2003. Image registration methods: a survey. In: *Image and vision computing*, Vol. 21, No. 11, pp. 977-1000.