AGILE Pre-conference workshop
"Bridging space, time, and semantics in GIScience"
Wageningen, The Netherlands, 9 May 2017

Knowledge-based Automatic Feature Recognition from Point Clouds in Urban Area

Xu-Feng XING
Laval University
Dept. of Geomatics Sciences
1055, avenue du Séminaire,
Bureau 1315, Québec, Canada
xufeng.xing.1@ulaval.ca

Mir-Abolfazl Mostafavi
Laval University
Dept. of Geomatics Sciences
1055, avenue du Séminaire, Bureau
1342, Québec, Canada
Mir-Abolfazl.Mostafavi@scg.ulaval.ca

Abstract

Advance in LiDAR technologies allows collection of a huge volume of data with high resolution for different applications. Automatic 3D modeling and feature recognition of LiDAR point clouds are required for applications ranging from virtual and augmented reality, 3D simulation and 3D gaming to the mobility of people with disabilities where detailed models of the environment are required for efficient accessibility assessment of urban places. 3D modeling from LiDAR data based on manual methods is not efficient, especially for real-time applications. Automatic knowledge-based 3D modeling and feature recognition have the potential to meet the requirements of these applications. This paper presents an integrated approach for automatic segmentation and feature recognition from LiDAR point clouds combining geometric approaches as well as qualitative knowledge about objects in complex urban scenes. This approach is hierarchical and allows automatics recognition of objects and their components based on the granularity of the knowledge base. Then, to demonstrate the validity of the proposed approach, a case study is presented and discussed at the end of the paper.

Keywords: Point clouds, automatic feature recognition, automatic segmentation, knowledge base, semantic reasoning

1 Introduction

Recent advances in LiDAR technologies allowed collection of a huge volume of data with high resolution for different applications ranging from urban planning, land surveying (Yang and Dong, 2013), robotic self-navigation, virtual and augmented reality, 3D simulation and 3D gaming to the mobility of people with disabilities. Compared to the time-consuming and expensive manual creation of 3D models of urban areas, semi-automatic and automatic 3D modeling from LiDAR point clouds are much more efficient. Due to the variety of objects and the complexity of their shape, manual modeling process from LiDAR point clouds is very time-consuming and costly compared to the data collection operations (Knaak, 2012). For real-time applications, such as autonomous cars and robots self-navigation, efficient and automatic 3D model of the surrounding dynamic environments is a prerequisite for on-the-fly decision making.

Automatic segmentation of point clouds is a crucial step for the automatic 3D geometric modeling from LiDAR point clouds (Pfeifer and Briese, 2007). Segmentation is a process of separating points into groups where each group of points belongs to the same surface is given the same label (Pu and Vosselman, 2006). The points in a group may belong to an object or a part of the object with a specific semantic meaning. For those objects with regular geometric shapes in an urban scene, the selection of segmentation algorithm relies on the knowledge about the type of the object (concept name and semantics, attributes, function, etc.) and its geometric properties. Following the segmentation process, the object components with regular shapes can be identified as geometric primitives (such as plane, sphere, cylinder). Moreover, the geometric information of components of the object (e.g. dimension information including length, width, height and area), topological relations with other components such as perpendicular, coplanar and parallel can be obtained. These sets of information are important for the feature recognition step. In this step, critical components of objects (e.g. building components including roof, wall, window and door) are recognized using semantic information in the knowledge base and integrated into a semantically enriched 3D geometric model of an urban scene. Semantically enriched 3D geometric models are not only necessary for efficient 3D modeling from point clouds, but also they are important for their applications. For example, people with disabilities using wheelchairs for their mobility need semantic information on objects for their navigation in an indoor environment. They need semantic information to distinguish between elevators rather than staircases when they plan to move between different floors.

Knowledge-based methods for automatic 3D modeling and feature recognition from point clouds of urban scenes have been developed and experimented in recent years. Pu et al.(Pu and Vosselman, 2009) used knowledge about buildings components as constraints to extract their important components (e.g. roof, wall, door, window) from LiDAR point clouds. Hence, the resulted building models provide detailed information on geometric and semantic properties of the components. Hmida et al.(Hmida et al., 2012) developed a knowledge-based object detection approach for railway infrastructure detection from point clouds. The knowledge base comprised of ontology and semantic rules represents expert knowledge about the railway objects. The knowledge of objects in the scene is used for guiding data processing algorithms and for semantic annotation of the model. Despite these efforts, current knowledge-based solutions for automatic feature recognition have limitations when applied in complex urban scenes. This is mainly due to the diversity of objects types and the complexity of their structure in such complex 3D environments. These complexities limit the capacity of predefined constraints or semantic rules for recognizing objects and their components in a complex urban scene.

In this paper, we propose a new knowledge-based solution for automatic segmentation and feature recognition from point clouds that consider the specific complexities of an urban scene. In this approach, first, a knowledge base for describing objects and their properties in urban scenes is built. Then appropriate knowledge for automatic segmentation and feature recognition are provided in the steps of automatic segmentation and object recognition. The qualitative knowledge and rules may include geometric characteristics of objects extracted from point clouds for the selection of segmentation algorithms as well as for the validation of object recognition results obtained from Support Vector Machine learning algorithms.

The remainder of this paper is organized as follows: Section 2 presents an overview of the proposed method and describes its main steps. Section 3 presents a case study and obtained results based on the proposed solution. Finally, the conclusions and future works are presented in section 4.

2 Overview of Proposed Method

Semantic information from 3D complex urban scenes is essential for enriched 3D geometric models from 3D point clouds and for their applications. Here we propose to benefit from semantic information about objects in urban scenes to improve automatic 3D modeling and feature recognition processes from 3D point clouds. To do so, first, we need to conceive a knowledge base that contains common knowledge about objects and their characteristic for object recognition from point clouds. Hence, the knowledge base is composed of concepts and constraints for feature recognition, which are specified in an ontology and semantic rules. Each concept includes information on its name, definition, properties and its functional roles. It also includes information on its spatial and temporal semantics including geometric shape dimension, relations, geometric properties and components. Metric and topological relationships between objects and between their components are important qualitative information included in the ontology. The information related to geometric characteristic and topological relations that can help to distinguish object types in point clouds are used to define semantic rules that will be used later in automatic modeling and feature recognition process. The knowledge base is formalized and represented using W3C Web Ontology Language (OWL) and Semantic Web Rule Language (SWRL). Based on the semantic rules and semantic information on the object types, a semantic reasoning approach is used for 3D modeling and object recognition processes. One of the contributions of our work is that we integrate qualitative knowledge into the automatic segmentation and semantic feature recognition from LiDAR point clouds. Hence, the proposed approach bridge between semantic description of an urban scene and automatic segmentation of point clouds obtained from the scene. In addition, the obtained 3D model can be annotated semantically at different levels of details.

As shown in Figure 1, the proposed framework for knowledge-based automatic segmentation and feature recognition from point clouds is composed of a knowledge base and several other modules. During automatic segmentation and feature recognition processes, the knowledge base provides the required information to other components. The descriptions of main steps in the framework are as follows:

- In rough classification step, the classification of object is defined by their spatial information as described in section 2.1.
- In the step of recognizing objects, some geometric properties for different segments are extracted from point clouds to recognize object types using a Support Vector Machine Learning algorithm according to the properties of concepts defined in knowledge base (see section 2.2).
- In the segmentation step, appropriate segmentation algorithm is selected and used to segment specific types of objects (see section 2.2).
- In the feature recognition step, the predefined semantic rules are employed for reasoning the object semantic features (see section 2.3).
- In the validation step, the consistency check between the extracted information and the predefined properties of specific object types validates the recognition process.
- After the validation, the segmentation results are transformed into the individuals of concepts for representing object components in the knowledge base. For example, the geometric properties are transformed into the properties of individuals and the topological relationships are transformed into relations among individuals. Similarly, the higher level semantic information of objects are transformed as well.

2.1 Knowledge base

In the knowledge base, concepts are structured according to an ontology that represents an urban scene. The concepts are hierarchically structured. Their granularity is defined based on the level of details need for a domain of application. The organization of the concepts at different levels of the granularity can be done from different perspectives. In this paper, we organize the levels of details of the ontology using three perspectives: 1) ground related concepts, 2) concepts to support automatic segmentation and feature recognition from point clouds, and 3) concepts related to the components of an object. For the propose of recognizing the object from point clouds, the ground points should firstly be removed. Because the objects with low elevation have a close relationship with ground, the objects in urban scene are classified into over-ground, near ground and ground classes. Based on these classes, concepts representing the object in urban scene are organized in these classes. In the next level, concepts describe the components of objects are added into the ontology. According to this structure, concepts can be organized in different levels of details, which is adaptable to the feature recognition and the creation of 3D semantically enriched geometric models at different levels of details (Figure 2). If a given application requires more detailed 3D models, the concepts in the ontology can be detailed further to better fit the needs described by the users (Biljecki et al., 2014).

The geometric properties are primarily characterized to help to recognize objects from segmentation results. The concepts related to the 3D geometric primitives are created in a separated module in the ontology to represent the spatial semantics associated with the segments represented by common geometric shapes (Figure 3).

For representing the topological relations among object components, we choose the extended RCC (Region Connection Calculus) topological models to represent the topological relation among planar segments in 3D space (for more details in (Xing et al., 2016)). The topological relations are formally represented as the properties in the ontology. Based on the extended RCC topological models in 3D space, the topological relations between two planar segments (A and B) are composed of four parts:

1) Spatial relation of two planes, including “Parallel”, “Coplanar” and “Intersect”. Here we will discuss the intersection case;

Figure 1 Proposed knowledge-based automatic segmentation and feature recognition framework

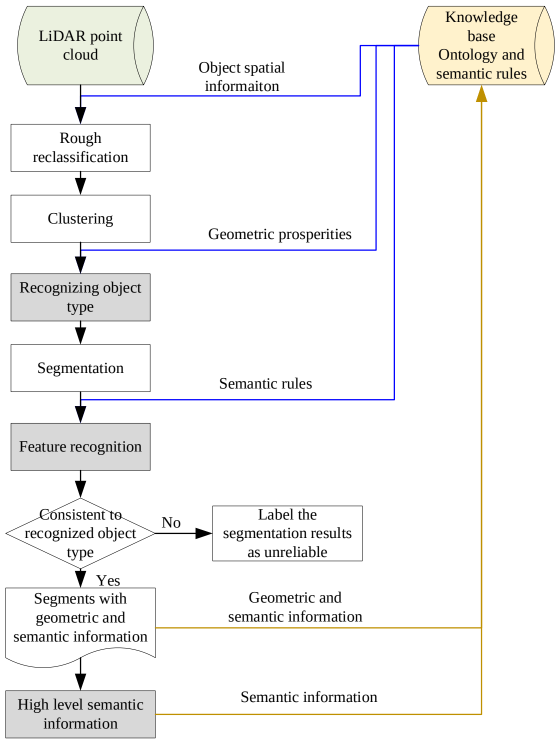
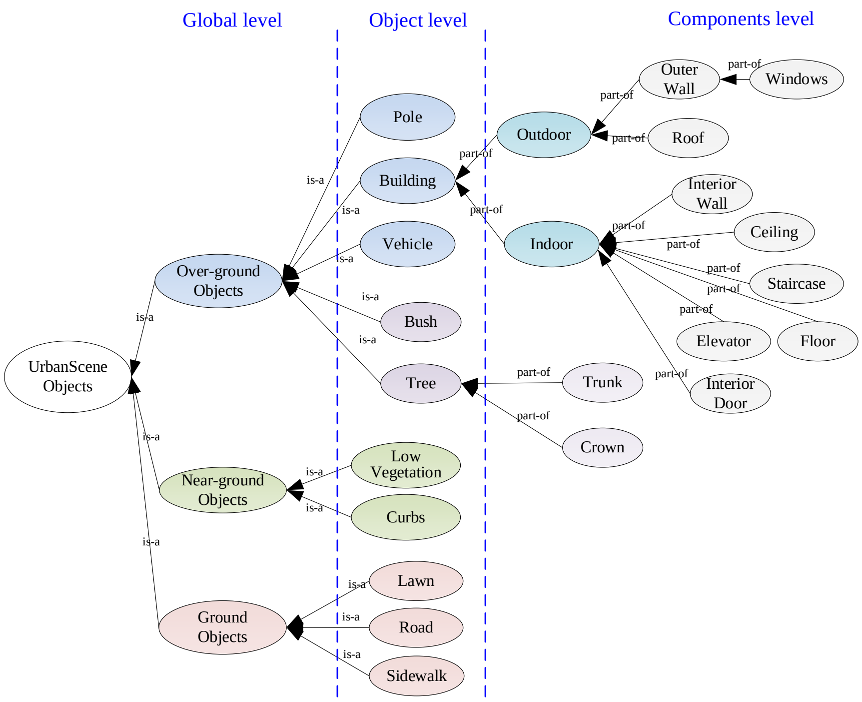
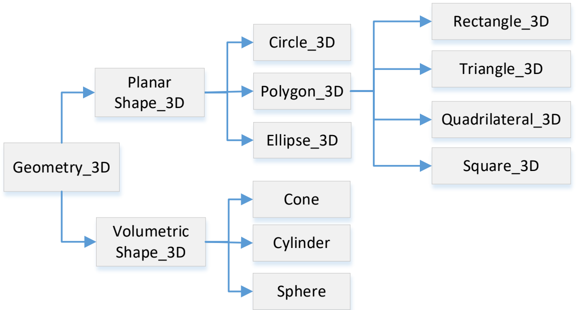


Figure 2 Different levels of the ontology describing an urban scene in the knowledge base



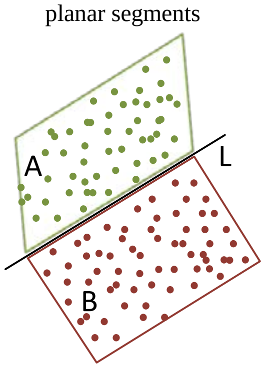
2) The topological relation between planar segment A and the intersection line (L) of two planes. The relations contain “Disjoint”, “Meet” and “Overlap”.
3) The topological relation between planar segment B and L. The relations contain “Disjoint”, “Meet” and “Overlap” as well;
4) The topological relations between the common part of A and L and the common part of B and L. The possible relations are “Disjoint”, “Meet”, “Overlap”, “Cover”, “CoveredBy” “Equal”, “Contain” and “ContainedBy”.

Figure 3 Concepts for describing geometric primitives



According to this way of describing the topological relations of two planar segments, a common topological relationship between planar segment A and B in Figure 4 is “Intersect-Meet-Meet-Equal”. The semantic representation of these topological relationships in the knowledge base is used for semantic reasoning in feature recognition.

Figure 4 An example of topological relations between two planar segments



2.2 Automatic Segmentation of Point Cloud

In segmentation step, the knowledge about the nature of objects helps to select appropriate segmentation algorithm for specific types of objects. For this purpose, first, a clustering algorithm based on the Euclidean distance partitions a point cloud into clusters in which points close to each other are grouped together. A preliminary analysis of the cluster allows extracting some geometric properties related to the cluster. Then we use a Support Vector Machine(SVM) learning algorithm to recognize the object type from the geometric properties of object. While man-made objects have regular shapes (e.g. buildings) and are generally composed of large planar segments. Natural objects such as trees have more complex and irregular shapes and it is generally difficult to detect large planar segments in those objects. Thus, we use Difference of Normals (DoN) (Ioannou et al., 2012) to extract the geometric characteristics of objects. For each point in a point cloud, a large radius is firstly used to select neighboring points for the estimation of surface normal. Then we use a small radius to estimate the surface normal at the same point. Finally, the difference between these two normals are calculated to analyze the planarity of the surface defined by the selected neighboring points. The characteristics of surface normal for a cluster are used to train the prediction model of SVM. After training the model, geometric properties of new clusters are extracted to determine their object types, the object recognition results are then expressed as a probability.

Following the identification of object type for a cluster, an appropriate segmentation algorithm is chosen to segment the cluster. For decreasing the computational cost of RANdom Sample Consensus (RANSAC), the region-growing segmentation algorithm is firstly applied to find the smooth surfaces from clusters. Then shape-base segmentation algorithm, for example, RANSAC can automatically detect common geometric shapes, such as plane, sphere, cone, cylinder etc. Finally, the components of objects are segmented as geometric primitives. To validate the correctness of object recognition from clusters, feature recognition is needed to check the object types obtained by SVM algorithm.

2.3 Feature Recognition

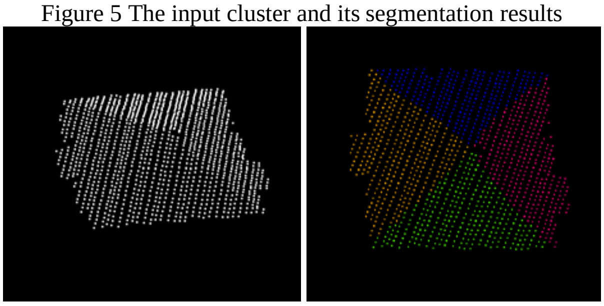
Based on the segmentation results, the knowledge about the components can be used to recognize object components. For this purpose, we use semantic rules defined in the knowledge base. For a planar segment, its dimension, spatial relations with other planar segments are used to reason about the component and its nature. According to common knowledge about objects, we list some important properties of objects to guide the definition of semantic rules. If the semantic information of object components after semantic reasoning is consistent with the object type information obtained by SVM algorithm, then the object type and segmentation results are consistent and valid. These semantic features are updated into the knowledge base as well to help with the reasoning process for other objects in the further.

When the knowledge of objects components is obtained, it is possible to get the higher level knowledge about objects. For example, when all the components of buildings roofs are segmented and their topological relations are defined, the roof shapes of buildings can be recognized. This higher level knowledge on buildings potentially can be used to improve the quality of geometric models and to ensure the right topological relations defined with other building components.

3 Experimental Results

To demonstrate the validity of the proposed approach, a case study is presented. Here, a cluster obtained after clustering an airborne LiDAR point cloud data set is selected to test our proposed solution of automatic segmentation and feature recognition. Following the steps of our method, the geometric properties of this cluster are evaluated by DoN of point clouds. The extracted geometric properties of the cluster allowed us to conclude that this cluster might be labeled as building type. Furthermore, the prior knowledge about airborne LiDAR allows us to conclude that the cluster recognized as building type should be the roof component of the buildings. For man-made objects, plane-based segmentation algorithms are chosen to segment this cluster. After the processing of the segmentation using the region growing and RANSAC algorithms, several planar components are extracted from this cluster (Figure 5). Then, the feature recognition is applied on these planar components. We use the knowledge about roof in the knowledge base to validate whether these planar segments are roof components. This include not only geometric properties of a roof but also a set of semantic rules that present common knowledge on geometric properties and relations of the roof with other components of a building. In this particular case, we verify if the planar segments are above the ground and they are not vertical to the ground. Then we conclude that the planar segments are indeed roof components and at the same time, we conclude that the building type recognized by SVM algorithm is valid.

Figure 5 The input cluster and its segmentation results



Now we have segmentation results and their geometric and semantic information. we can create topological relations among them. First, the common part of planar segment and the intersection line are extracted. The relations between planar segments and the line are “Meet” relation. As shown in Figure 6, all the common parts of planar segments and the intersection line represent their boundaries. The determination of the topological relations between these two common parts (points or line segments) on the line require the relations of their endpoints. For example, for the case of blue and rose red planar segments, the endpoints of two line segments are extracted. As shown in Figure 7, the distances between two nearby endpoints of two line segments are 0.25 m and 0.15 m, which are smaller than the average distance between points that is around 0.5 m. Moreover, the proportion of the length of short and long line segments is 0.944. Based on this information, we can consider their relations as “Equal”. Similarly, the topological relationships of other line segments on the intersection line are “Equal”. Finally, the topological relations of nearby planar components are represented as “Intersect-Meet-Meet-Equal”.

Now we have the topological relations among components. Next we use the topological relations among the components to reason higher level seamntic information on the objects. We define a set of rules to recognize the roof shape based on their geometric properties and the topological relations between its components as presented in the following rules. Based on the geometric properties of segmentation results and their topological relations, the pyramid hip roof is defined as that four planar roof components with triangle boundaries have “Intersect_Meet_Meet_Equal” relations with their neighboring roof components. “Set” indicates the group of planar components. “PlaneShape_3D” represents the concept of planar segment. “PyramidHipRoof” means the hip roof shape. It is translated into the following semantic rule. This rule allows recognizing pyramid hip roof shape from a group of planar roof components based on their geometric shape and topological relationships.

Set(?B), PlaneShape_3D(?Pr1), PlaneShape _3D(?Pr2), PlaneShape _3D(?Pr3), PlaneShape _3D(?Pr4), isInSet(?Pr1, ?B), isInSet(?Pr2, ?B), isInSet(?Pr3, ?B), isInSet(?Pr4, ?B), Triangle(?Pr1), Triangle(?Pr2), Triangle(?Pr3), Triangle(?Pr4), isIntersect_Meet_Meet_Equal (?Pr1, ?Pr4), isIntersect_Meet_Meet_Equal (?Pr1, ?Pr2), isIntersect_Meet_Meet_Equal (?Pr1, ?Pr3), isIntersect_Meet_Meet_Equal (?Pr2, ?Pr1), isIntersect_Meet_Meet_Equal (?Pr2, ?Pr3), isIntersect_Meet_Meet_Equal (?Pr2, ?Pr4), isIntersect_Meet_Meet_Equal (?Pr3, ?Pr1), isIntersect_Meet_Meet_Equal (?Pr3, ?Pr2), isIntersect_Meet_Meet_Equal (?Pr3, ?Pr4), isIntersect_Meet_Meet_Equal (?Pr4, ?Pr1), isIntersect_Meet_Meet_Equal (?Pr4, ?Pr2), isIntersect_Meet_Meet_Equal (?Pr4, ?Pr3), ComponentsofRoof(?Pr1), ComponentsofRoof(?Pr2), ComponentsofRoof(?Pr3), ComponentsofRoof(?Pr4) -> ***PyramidHipRoof(?B)***

Figure 6 The extracted points on the intersection of planar segments

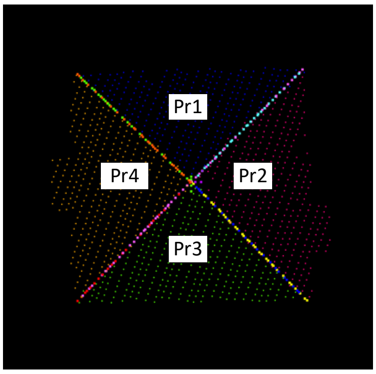
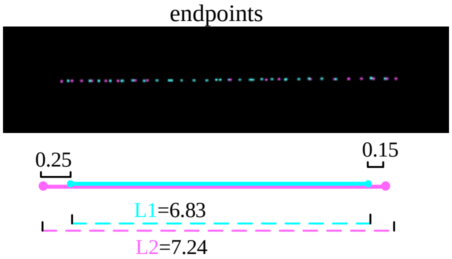


Figure 7 The points of line segments and the relations of their endpoints



Using this rule, the roof shape “Pyramid Hip Roof” can be reasoned from segmented planar components based on the knowledge base.

4 Conclusions and Future Work

In this paper, we presented a knowledge-based approach for automatic segmentation and recognition of objects in complex urban scene from a point cloud. The knowledge base consists of information from an ontology describing the urban scene and semantic rules defined using common knowledge on the object types, their relations, and geometric and semantic properties of those objects. According to the proposed approach, knowledge about specific types of objects is used to recognize object types from the clusters. Using the object recognition results, the appropriate shape-based segmentation algorithms are chosen to segment objects in the clusters. Based on the segmentation results and their topological relations, a higher level knowledge of objects can be obtained using the semantic rules defined in the knowledge base.

This work is a part of an ongoing research. Future work will mainly focus on the improvement of recognition step for more diversified object types from clusters. We will also conduct more research work on resolving the recognition of uncertain cases and on the automatic generation of 3D semantically enriched geometric models using qualitative knowledge from a scene observed by LiDAR technology.

Acknowledgement

This research is supported jointly by Natural Sciences and Engineering Research Council of Canada (NSERC) and the China Scholarship Council. The authors would like to gratefully acknowledge the dataset provider for the experimentations presented in this paper.

Reference

Biljecki, F., Ledoux, H., Stoter, J. & Zhao, J. (2014). Formalisation of the level of detail in 3D city modelling. *Computers, Environment and Urban Systems,* 48**,** 1-15.

Hmida, H. B., Cruz, C., Boochs, F. & Nicolle, C. (2012). Knowledge Base Approach for 3D Objects Detection in Point Clouds Using 3D Processing and Specialists Knowledge. *International Journal on Advances in Intelligent Systems,* 5**,** 1-14.

Ioannou, Y., Taati, B., Harrap, R. & Greenspan, M. Difference of Normals as a Multi-scale Operator in Unorganized Point Clouds. 2012 Second International Conference on 3D Imaging, Modeling, Processing, Visualization & Transmission, 2012.

Knaak, T. 2012. *Two Perspectives on LiDAR Technology Market Adoption* [Online]. LIDAR MAGAZINE. Available: http://www.lidarmag.com/content/view/8864/199/.

Pfeifer, N. & Briese, C. (2007). Geometrical aspects of airborne laser scanning and terrestrial laser scanning. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences,* 36**,** 311-319.

Pu, S. & Vosselman, G. (2006). Automatic extraction of building features from terrestrial laser scanning. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences,* 36**,** 25-27.

Pu, S. & Vosselman, G. (2009). Knowledge based reconstruction of building models from terrestrial laser scanning data. *ISPRS Journal of Photogrammetry and Remote Sensing,* 64**,** 575-584.

Xing, X. F., Mostafavia, M. A. & Wang, C. (2016). Extension of RCC Topological Relations for 3D Complex Objects Components Extracted from 3D LiDAR Point Clouds. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.,* XLI-B3**,** 425-432.

Yang, B. & Dong, Z. (2013). A shape-based segmentation method for mobile laser scanning point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing,* 81**,** 19-30.