Toward Knowledge-based Automatic 3D Spatial Topological Modeling from LiDAR Point Clouds for Urban Areas

Thèse

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Résumé

Le traitement d'un très grand nombre de données LiDAR demeure très coûteux et nécessite des approches de modélisation 3D automatisée. De plus, les nuages de points incomplets causés par l’occlusion et la densité ainsi que les incertitudes liées au traitement des données LiDAR compliquent la création automatique de modèles 3D enrichis sémantiquement. Ce travail de recherche vise à développer de nouvelles solutions pour la création automatique de modèles géométriques 3D complets avec des étiquettes sémantiques à partir de nuages de points incomplets. Un cadre intégrant la connaissance des objets à la modélisation 3D est proposé pour améliorer la complétude des modèles géométriques 3D en utilisant un raisonnement qualitatif basé sur les informations sémantiques des objets et de leurs composants, leurs relations géométriques et spatiales. De plus, nous visons à tirer parti de la connaissance qualitative des objets en reconnaissance automatique des objets et à la création de modèles géométriques 3D complets à partir de nuages de points incomplets.

Pour atteindre cet objectif, plusieurs solutions sont proposées pour la segmentation automatique, l'identification des relations topologiques entre les composants de l'objet, la reconnaissance des caractéristiques et la création de modèles géométriques 3D complets.

(1) Des solutions d'apprentissage automatique ont été proposées pour la segmentation sémantique automatique et la segmentation de type CAO afin de segmenter des objets aux structures complexes.
(2) Nous avons proposé un algorithme pour identifier efficacement les relations topologiques entre les composants d'objet extraits des nuages de points afin d'assembler un modèle de Représentation Frontière.
(3) L'intégration des connaissances sur les objets et la reconnaissance des caractéristiques a été développée pour inférer automatiquement les étiquettes sémantiques des objets et de leurs composants. Afin de traiter les informations incertitudes, une solution de raisonnement automatique incertain, basée sur des règles représentant la connaissance, a été développée pour reconnaître les composants du bâtiment à partir d'informations incertaines extraites des nuages de points.
(4) Une méthode heuristique pour la création de modèles géométriques 3D complets a été conçue en utilisant les connaissances relatives aux bâtiments, les informations géométriques et topologiques des composants du bâtiment et les informations sémantiques obtenues à partir de la reconnaissance des caractéristiques.

Enfin, le cadre proposé pour améliorer la modélisation 3D automatique à partir de nuages de points de zones urbaines a été validé par une étude de cas visant à créer un modèle de bâtiment 3D complet. L'expérimentation démontre que l'intégration des connaissances dans les étapes de la modélisation 3D est efficace pour créer un modèle de construction complet à partir de nuages de points incomplets.

Abstract

The processing of a very large set of LiDAR data is very costly and necessitates automatic 3D modeling approaches. In addition, incomplete point clouds caused by occlusion and uneven density and the uncertainties in the processing of LiDAR data make it difficult to automatic creation of semantically enriched 3D models. This research work aims at developing new solutions for the automatic creation of complete 3D geometric models with semantic labels from incomplete point clouds. A framework integrating knowledge about objects in urban scenes into 3D modeling is proposed for improving the completeness of 3D geometric models using qualitative reasoning based on semantic information of objects and their components, their geometric and spatial relations. Moreover, we aim at taking advantage of the qualitative knowledge of objects in automatic feature recognition and further in the creation of complete 3D geometric models from incomplete point clouds.

To achieve this goal, several algorithms are proposed for automatic segmentation, the identification of the topological relations between object components, feature recognition and the creation of complete 3D geometric models.

(1) Machine learning solutions have been proposed for automatic semantic segmentation and CAD-like segmentation to segment objects with complex structures.
(2) We proposed an algorithm to efficiently identify topological relationships between object components extracted from point clouds to assemble a Boundary Representation model.
(3) The integration of object knowledge and feature recognition has been developed to automatically obtain semantic labels of objects and their components. In order to deal with uncertain information, a rule-based automatic uncertain reasoning solution was developed to recognize building components from uncertain information extracted from point clouds.
(4) A heuristic method for creating complete 3D geometric models was designed using building knowledge, geometric and topological relations of building components, and semantic information obtained from feature recognition.

Finally, the proposed framework for improving automatic 3D modeling from point clouds of urban areas has been validated by a case study aimed at creating a complete 3D building model. Experiments demonstrate that the integration of knowledge into the steps of 3D modeling is effective in creating a complete building model from incomplete point clouds.

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Acronyms

4IM	4-Intersection Model
9IM	9-Intersection Model
Abox	Assertional axioms
AI	Artificial Intelligence
BPA	Basic Probability Assignments
B-Rep	Boundary Representation model
CityGML	OGC City Geography Markup Language
CRF	Conditional Random Fields
CSG	Constructive Solid Geometry
DAML	DARPA Agent Modelling Language
DC	Disconnected
DDA	Disability Discrimination Act
DE-9IM	Dimensionally Extended 9-Intersection Model
DL	Description Logics
DoN	Difference of Normal
D-S	Dempster-Shafer
EC	Externally Connected
EQ	Equal
GIS	Geographic Informaiton System
GIScience	Geographic Information Science
GPS	Global Positioning System
IMU	Inertial Measuring Unit
JEPD	Jointly Exhaustive and Pairwise Disjoint
KR	Knowledge Representation
LiDAR	Light Detection And Ranging
LOD	Level Of Detail
MLESAC	Maximum Likelihood Estimation SAmple and Consensus
MRF	Markov Random Fields
MSAC	M-estimator SAmple and Consensus
NTPP	Non-Tangential Proper Part

OIL	Ontology Inference Layer
OWL	Web Ontology Language
PCA	Principal Component Analysis
PO	Partial Overlap
PROSAC	Progressive Sample and Consensus
QSR	Qualitative Spatial Reasoning
RANSAC	RANdom SAmple Consensus
RBNN	Radially based Nearest Neighbors
RBox	relational axioms
RCC	Region Connection Calculus
RDF	Resource Description Framework
SVD	Singular Value Decomposition
SVM	Support Vector Machine
SWRL	Semantic Web Rule Language
Tbox	Terminological axioms
TIN	Triangulated Irregular Network
TPP	Tangential Proper Part
VGE	Virtual Geographic Environments

Acknowledgments

With a passion for academic research, I came from as far as China to start a PhD at Université Laval, Canada. Experience of studies and life in Québec gave me the spiritual endurance and academic knowledge necessary to meet all the possibilities of my future life. Personal achievement in this career cannot be accomplished without help from surrounding people in all aspects of academics, education and psychological life, and the encouragement and support from family.

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Foreword

This PhD thesis contains seven chapters, including five scientific articles (Chapters 2 to 6) that either have been published, submitted or to be submitted. The author of this thesis, Xu-Feng XING, is the main author of these articles. The contributions of the author of these articles were to perform all the experimental work, the preparation and the analysis of the data, and to write the manuscripts. The co-authors' contributions consist of the revision, correction and commenting of these articles.

Chapter 2 presents pointwise semantic segmentation of urban scenes from point clouds. This article was authored by Xu-Feng XING, Mir Abolfazl Mostafavi, Geoffrey Edwards, and Nouri Sabo. Published on 3D GeoInfo Conference 2019 in Singapore.

Chapter 3 presents the segmentation of buildings with complex structures from point clouds of urban scenes. This article was authored by Xu-Feng XING, Mir Abolfazl Mostafavi, Geoffrey Edwards, and Nouri Sabo. To be submitted to a scientific journal.

Chapter 4 presents topological relations for 3D complex object components extracted from point clouds. This article was authored by Xu-Feng XING, Mir Abolfazl Mostafavi, and Chen WANG. It was published in The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences in 2016.

Chapter 5 presents a knowledge base comprised of ontology and semantic rules aimed at automatic feature recognition from point clouds in support of 3D modeling. This article was authored by Xu-Feng Xing, Mir Abolfazl Mostafavi, and Seyed Hossein Chavoshi. It was published in the International Journal of Geo-Information in 2018.

Chapter 6 presents rule-based uncertain reasoning for recognizing building features from point clouds. This article was authored by Xu-Feng XING, Mir Abolfazl Mostafavi, Geoffrey Edwards, and Nouri Sabo. To be submitted to a scientific journal.

Introduction

1 Research Context

With the expansion of cities and the rapidly changing cityscape, authorities and decision-makers agree with the necessity for 3D digital city models and geographic information systems (GIS) for sustainable development and better management of cities (AAM, 2011). Thus, the creation of three-dimensional (3D) models for urban areas and related 3D modeling technologies have drawn increasing attention over recent years. Considering the wide range of applications, 3D models for urban areas should not only display realistic models of objects in the city but contain accurate and reliable geographic, geometric, semantic and topological information (Gröger, 2012; Yang, 2010). Due to its requirement for multidimensional urban information (spatial, social, economic, etc.), urban planning provides a good example of the use of 3D modeling for urban areas. Additionally, 3D models are widely applied in other fields, such as health studies, water conservancy, urban management, geological disaster management, transportation, and environmental protection, to name just a few (Qin, 2010). Other aspects related to 3D spatial analysis include skyline planning, sunshine analysis, emergency response for fire disaster, and the prediction for rainwater runoff and flooding. New applications, such as the design and implementation of sensor networks in city planning, visual and augmented reality, and the measurement of city accessibility, also require detailed and precise 3D models for urban areas. The extensive application of 3D modeling is the primary motivation for this research.

Efficient 3D spatial data processing and modeling are made possible thanks to advances in information technologies integrated with methods and tools in geomatics and computer vision. Although 3D models are becoming more widespread in diverse fields, 3D modeling methods and technologies have not been able to catch up with the diverse requirements of applications. Spatial data acquisition technologies such as LiDAR (Light Detection And Ranging) technology provide users with massive data sets in a very short period of time, but efficient exploitation of these data requires appropriate modeling methods and techniques. Manual 3D modeling is an extremely time-consuming, labor-intensive process (Gool, 2007) and hence is not cost-effective. More importantly, the incompleteness caused by occlusion and uneven point density in point clouds lead to the challenges of the automatic creation of complete 3D geometric models. Thus, the improvement of automatic 3D modeling capabilities has become a pressing need to meet emerging requirements in time-sensitive applications.

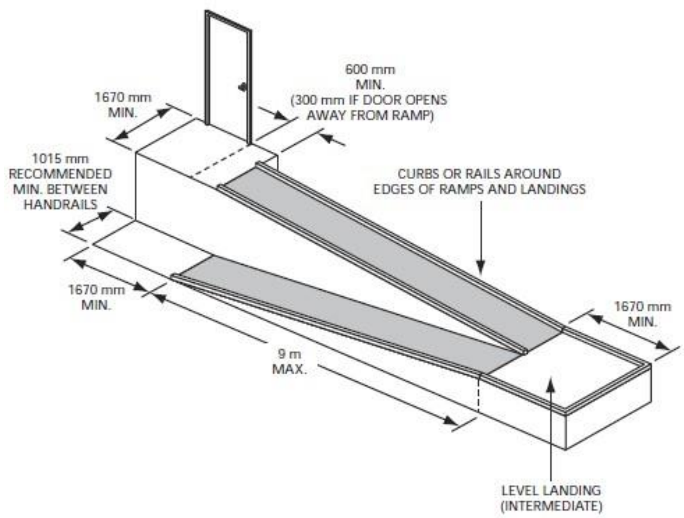
The Necessity of 3D Modeling of Urban Areas

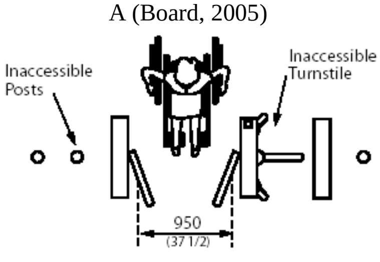
The rapid expansion of our cities increasingly necessitates methods and tools for their efficient management. Integrating advanced geographic information technologies into city management will contribute to the delivery of new services for authorities, decision-makers, and the general public. 3D modeling technologies attempt not only to create intuitive geometric 3D models of urban areas but also focus on integrating useful semantic information (for example, semantic meanings of city facilities) to geometric models. Using such technologies, researchers concerned about the problems caused by rapid urban development can analyze issues of interest to them, such as traffic jams, city zoning issues, and planning. Government managers can visually manage the city's infrastructure and make decisions in light of comprehensive multi-source information. As for the public, they can enjoy convenient information inquiry service. From the perspective of information sharing, a low-cost way to share all aspects of social information with the population can be provided for making information transfer faster and increasing the value of information. Hence, 3D modeling for urban areas is necessary to meet the emerging requirements related to scientific research, decision-making and information distribution.

A typical example of the application of 3D city models is for urban planning. Indeed, in the process of urban planning, information must include spatial and non-spatial components, qualitative and quantitative features, and cover a wide range of physical, social, and economic attributes (Harris, 1993; Wang, 2007a). For the purpose of facilitating the planning and the analysis of existing complex urban problems, the necessity for information collected from diverse aspects is obvious. Most importantly, this information needs to be integrated and shared with decision-makers and researchers (Wang, 2007a). Therefore, creating 3D models of urban areas composed of geometric information, geo-referenced information and qualitative and quantitative semantic information is a fundamental research task for further studies in urban planning. For instance, based on a specific 3D city model, 3D building models with different levels of detail (LOD) (Biljecki, 2014) can be used in predicting the heating energy demand (Strzalka, 2011).

Navigation aid in urban areas is an increasing demand in large cities due to the complexity of intertwined city roads, freeway entrances, viaducts, and transportation hub entrances during the expansion of cities. 3D models of transportation facilities provide a display closer to reality and better visual aid to drivers than 2D maps. In addition, indoor navigation requires detailed 3D models of building interiors, including geometric information related to floors, doors, stairs and so on, their semantic labels and the topology of building structures. With the increasing attention on the rights of people with disabilities, city accessibility issues, especially in relation to people with disabilities or special needs, are becoming more important. Accessibility is the degree to which a product, device, service, or environment is available to as many people as possible. Furthermore, accessibility can be viewed as the "ability to access" and benefit from some system or entity (Wikipedia). Such issues were addressed in the “Disability Discrimination Act (DDA)” in the UK (1995), and the Disabilities Act in the USA (1990) (updated guidelines from http://www.access-board.gov). Other countries such as Canada, Australia, New Zealand, and Japan have also taken steps to address disability rights (F Bromley, 2007). In fact, an ideal urban design should be accessible to all users, but current transit infrastructure is designed for the able-bodied, often leading to inconveniences and difficulties for those with disabilities (Audirac, 2008) (Figure I(A)). Comprehensive and appropriate LOD in 3D city models offers the potential to make special navigation services available for people with disabilities. This requires detailed accessibility measurement information (Figure I(B) and (C)). Indeed, in navigation service for people with disabilities, 3D city models should include the road topologies, all kinds of 3D models in urban areas and their topologies, geometric properties, and road conditions, as well as the width and height of passages, roughness, slope of ramps, obstacles, widths of roads, widths between obstacles, staircases, and semantic marks for special passages and facilities. As a result, detailed 3D models of urban areas are essential to widespread applications and the automation of 3D modeling for urban areas.

A (Board, 2005)





B (Stratford, 2004)

C (Stratford, 2004; Toronto, 2004)

Figure I (A) An example providing convenience for pedestrians, but blocking a blind person; (B) A special passage for wheelchairs; (C) Example of the detailed 3D model used for assisting the navigation of people with disabilities and for accessibility computation

Challenges Associated with Automatic 3D modeling of Urban Areas from LiDAR Point Clouds

For improving automatic 3D modeling from LiDAR point clouds in urban areas, the efforts made on pointwise semantic segmentation (classify point cloud at point level), CAD-like segmentation of objects (segment objects into components using geometric properties at component level), identifying topological relations between object components (topology between components), and feature recognition (the process of semantic labeling of objects and object components), all contribute to the automatic creation of semantically annotated 3D models at different levels of details (LODs). Due to the complexity of urban scenes and the volume of point clouds, research in several aspects will mitigate the difficulties of automatic 3D modeling of urban scenes from point clouds. Pointwise semantic segmentation of point clouds is a necessary step to know which types of objects are found in urban scenes because semantic segmentation seeks to partition a point cloud into semantically meaningful groups of points at the level of points, similar to semantic segmentation in images (Long, 2015). After pointwise semantic segmentation, CAD-like segmentation of each object attempts to group points associated with this object or object components into several groups with homogeneous properties. In this step, object components are segmented according to the similarities of points, such as geometric shapes, smoothness, or color. Following this step, it is necessary to identify topologies between object components to assemble a 3D Boundary Representation (B-Rep) model of an object from its components. This is helpful to create semantically annotated 3D maps that contain labels in addition to geometric information of objects (Lin, 2014; Rusu, 2009a), for example, a semantically enriched 3D building model for indoor navigation requires the topologies between building components. For creating semantically enriched 3D city models, recognizing objects and their components will provide semantic labels to objects at different LODs. However, the incompleteness of point clouds in urban scenes caused by occlusion or sparse point density makes it difficult to carry out pointwise semantic segmentation of complex urban scenes, CAD-like segmentation of objects, identification of topology among components, and feature recognition. It is hence challenging to create complete 3D models of urban scenes from incomplete point clouds. In summary, the main challenges of automatic 3D modeling of urban areas from point clouds are as follows:

1. Segmentation of objects from point clouds of urban scenes with uncertainties (uneven point density, incompleteness);
2. Extractions of shape and topology from segmentation results for creating a 3D B-Rep model;
3. Feature recognition from segmentation results at the object level and component level;
4. Creation of complete 3D geometric models from point clouds with uncertainties.

2 Problem Statement

LiDAR (NOAA) technology is capable of rapid scanning and recording of high-density point clouds in urban scenes. However, the time spent on fieldwork for LiDAR point cloud acquisition is out of proportion compared to the time for data processing. For some real-time applications, such as autonomous vehicles, automatic information extraction is necessary to make decisions. Similarly, real-time semantic 3D maps are prerequisites in the motion planning for robotic navigation based on object detection and the perception of dynamic changes of environments. Thus, automatic information extraction from point clouds is a necessary prerequisite for real-time applications.

LiDAR technology may provide enough detailed information for 3D urban environments. However, 3D automatic modeling of urban scenes from point clouds is a complex problem and it is a very complex process due to the fact that urban areas are composed of different man-made and natural objects. It is hence difficult to automatically produce complete 3D geometric models of urban scenes from point clouds based on geometric approaches (Abuhadrous, 2004; Heo, 2013; Li, 2012a; Moussa, 2010a). These complexities are also partly due to the occlusion problem which leads to incompleteness and non-uniform point density in the point clouds. It is challenging to automatically generate a complete 3D geometric model from an incomplete point cloud. The incomplete point cloud may cause additional problems, such as incomplete geometric shapes of components, incomplete and inaccurate shape boundaries of components, and incorrect topological relations between the components in a single object model (e.g., building). Moreover, the creation of complete 3D models with the help of the semantic information of objects and their components is a promising solution but it still requires further study.

A point cloud is composed of 3D points with their coordinates and other properties (such as intensity, classification, time, return number, number of returns, scan direction flag, scan angle rank, user data, and point source ID). The reconstruction of geometric 3D models of objects relies on the coordinates that record geometric shapes of objects in detail. However, the acquisition of semantic information on the objects and the creation of complete 3D geometric models of objects using semantic information also requires further processing of the geometric information of objects. In the following, we present in detail several steps for the automatic processing of LiDAR data including classification, segmentation, topology extraction, feature recognition and finally shape extraction.

Classification, Object Detection and Semantic Segmentation

Classification is the step of classifying the points in a point cloud into several different classes (e.g., ground, vegetation, buildings, etc.). The criteria for classification can be defined using the principles of LiDAR technology and knowledge about objects. For example, the property "number of returns" is a crucial criterion to separate vegetation from the terrain since laser pulses can be reflected several times. The classification of point clouds is a necessary step in 3D modeling of urban scenes.

Object detection attempts to know where the instances of objects in the images or point cloud are. The aim of object detection is to identify the locations of interested objects of a certain class, such as face detection in images, lane detection (Narote, 2018), and single-target tracking of a moving object for driverless car navigation (Held, 2016). Object detection focuses on the task of distinguishing the object of interest from others, for example, in the task of lane detection in images, the output must detect all the lanes rather than all the objects such as vehicles.

Semantic segmentation of images (Long, 2015) makes a prediction for each pixel and directly labels object classes at the pixel level. The difference between object detection and semantic segmentation is that semantic segmentation directly locates all objects and knows object classes at the same time. Similarly, pointwise semantic segmentation of point clouds (Hackel, 2016; Landrieu, 2018; Tchapmi, 2017) also gives a label to each point for understanding what objects are in present scenes in point clouds.

Classification, object detection and semantic segmentation of point clouds all try to group points belonging to a certain object together and they all contribute to the process of 3D modeling of point clouds. However, pointwise semantic segmentation of point clouds produces semantic labels at the level of points only.

Segmentation

Following the pointwise semantic segmentation of an urban scene, CAD-like segmentation is the process of partitioning a point cloud into neighboring regions with homogeneous properties where all points belonging to a group have the same meaningful label (Awwad, 2010; Rabbani, 2006). Via CAD-like segmentation, points with similar geometric properties can be considered as a segment. For instance, points belonging to the same geometric primitive such as a planar surface can be segmented according to a smoothness property. Additionally, CAD-like segmentation based on geometric properties is also a source of the semantic information necessary for most applications (Pfeifer, 2007).

The segmentation results are closely related to the quality (the completeness, density, and the precision of the measurement) of point clouds. Low quality point clouds make it difficult to choose appropriate parameters for the segmentation algorithms. Moreover, in a complex urban scene, a point cloud acquired by a mobile LiDAR scanner may be incomplete due to possible occlusions between objects or between object components. In addition, the diversity of the geometric characteristics of objects and the uncertainties in scanned point clouds can contribute to the complexity of the automatic segmentation of a point cloud. We need knowledge about objects, for example, object type and surface type (smooth or unsmooth), for the selection of appropriate segmentation algorithms and the determination of parameters. Therefore, knowledge about objects in urban scenes is required to improve the quality of automatic CAD-like segmentation.

Problems of CAD-like segmentation, such as over-segmentation, under-segmentation, and non-segmentation, may occur during the segmentation of point clouds of complex urban scenes. These problems occur when unsuitable segmentation algorithms are chosen, or inappropriate parameters are given to segmentation algorithms. For example, if a curved surface is segmented using a small curvature threshold, the surface will be divided into several patches and the surface will be over-segmented. If two coplanar walls that are disconnected in reality are segmented as one plane, it is called a case of under-segmentation. If several objects are not segmented from point clouds, it is a non-segmentation case (Rabbani, 2006). The case of over-segmentation could be processed in later steps of 3D modeling, for example, by aggregation. Under-segmentation and non-segmentation, however, cannot be easily corrected and will affect later steps. Hence, under-segmentation and non-segmentation should be eliminated to the maximum extent, and under-segmentation should be decreased simultaneously.

Topology Extraction

Topological relations between geographical objects in the urban scene are fundamental for the analysis of spatial relations in practical applications. In a 2D space, a spatial object could be abstracted as a point, a line segment or a region. Here a region is defined as a 2D cell that has a non-empty connected interior (Egenhofer, 1990a). Based on this definition, a region has an interior and a boundary. Topological relations between spatial objects can be derived based on the Region Connection Calculus (RCC) (Egenhofer, 1989; Egenhofer, 1991a; Egenhofer, 1991b). The Intersection Models are commonly accepted in the formalized description of topological relations, and they can be implemented in practical applications. The 4-Intersection Model (4IM), 9-Intersection Model (9IM) and Dimensionally Extended 9-Intersection Model (DE-9IM) were developed based on the intersection operation between boundaries and interiors of two regions. In the 9IM, the topological relations are represented as a 3x3 matrix. According to the value of elements in the matrix, eight relations are discernible, that is, disjoint, meet, overlap, contain, cover, containedBy, coveredBy and equal.

In a 3D space, the topological relations between 3D spatial objects are closely related to the way of representing 3D objects. A spatial object can be modeled as a solid geometry or represented by its boundaries, such as in the Constructive Solid Geometry (CSG) model and the Boundary Representation model (B-Rep) (Stroud, 2006). RCC topological relations can be extended to define relations between 3D objects in 3D space (Zlatanova, 2004). For example, RCC-3D (Albath, 2010b) and VRCC-3D+ (Sabharwal, 2011) are developed based on RCC to distinguish topological relations between 3D objects, such as non-occlusion, partial occlusion and complete occlusion relations in specific projected planes. The identification of topological relations between 3D objects relies on the projection operation in the XY, YZ and XZ planes. Therefore, the determination of topological relations depends on topological relations between 2D objects on projected planes in nature. However, these methods are not suitable for expressing the relations between components in a B-Rep model of an object. In a B-Rep model of an object, components can be represented as geometric primitives in 3D space. Object components can be abstracted by a 3D region with interior, boundaries as well as geometric properties in 3D space. Topological relations between 3D regions are fundamental to assemble a B-Rep model. For automatic 3D modeling process, the topological relations between object components in 3D space are necessary for applications such as in indoor navigation applications and robot motion planning. Hence, it is necessary to define new topological relations between object components.

Feature Recognition

As geometric features of objects (line, plane, cylinder, cone, sphere, etc.), the semantic information about objects and their components is called the semantic features. The process of recognizing semantic features from point clouds is called feature recognition. In fact, semantically enriched geometric models are required in some applications for supporting specific tasks such as finding a location in indoor navigation, routing for a mobile robot or finding routes for emergency evacuation. In 3D city modeling, the semantic features of buildings, such as walls, windows, doors, dormers, and balconies have been proposed in LOD4 building models in CityGML (Gröger, 2012). Therefore, automatic feature recognition from segmentation results is a key step for creating semantically enriched 3D models for an urban scene.

In 3D modeling of urban scenes from point clouds, the geometric properties of the object components and the topological relations between them must be obtained after the CAD-like segmentation. Indeed, the semantic information of object components is not easily extracted from segmentation results. Knowledge about each specific type of object is necessary to identify objects in point clouds. Alternatively, one could apply machine learning algorithms for feature recognition (Xiong, 2013). For example, in a simple indoor scene, machine learning method performs well to extract the semantics of objects. However, in a complex urban scene, a huge amount of training set is required to ensure the precision of the semantic labeling. In fact, it is hard to collect and process massive point clouds due to the limitation of computation capability and the cost of manually annotating point clouds. As a result, knowledge-based solutions for extracting semantic features from point clouds offer an alternative way to recognize the objects and their components. Knowledge about objects in urban scenes can be summarized and represented formally (e.g., via a formal ontology) in a knowledge base. Some predefined knowledge is essential to recognize an object and its components from the geometric features and the relations between components and their contextual information. In conclusion, the integration of formalized knowledge and semantic reasoning could be used to improve the automatic recognition of objects in a complex urban scene. It is important to mention that the uncertainties in the steps of segmentation and topology extraction should be considered during feature recognition as well.

Shape Extraction

The quality of the geometric model or shape of a 3D complex object depends on the quality of the geometric models of its components. After the segmentation step, a component of an object is represented as a segment. The point density directly affects the quality of shape extraction from each segment. For those incomplete point clouds caused by occlusion and non-uniform point density, it is difficult to extract accurate shapes for objects with complex shapes based on the algorithms for detecting boundaries from point clouds. In this case, the semantic information of object components may be helpful to determine the final geometric shapes of the components through the knowledge of geometric and topological relations between components. For example, for buildings, the inherent constraints (e.g., a roof is over the walls, a door is in a wall and its bottom touches a floor) may be used to recognize building components and in some cases improve or complete the geometric representation of the components. Thus, topological and geometric information of object components and their knowledge is required for the complete extraction and modeling of a complex scene.

In summary, challenges exist in all stages of automatic 3D modeling from point cloud especially in the presence of uncertain information caused by occlusion and non-uniform density of the point cloud. Due to the difficulty of segmenting point clouds, identification of topological relations, feature recognition and shape extraction based on segmentation results may be uncertain. Hence, the general problem addressed by this thesis is as follows:

The uncertainty and incompleteness of point clouds for complex urban scenes make automatic 3D modeling very challenging and affect significantly the quality of the 3D models.

This general problem can be divided into the following specific problems, which will be each addressed in turn:

- **The complexities of the urban scene, such as the variety of object types with different sizes and geometric shapes as well as problems in point clouds from those scenes (incompleteness and uncertainties), lead to over-segmentation, under-segmentation, and non-segmentation of point clouds in the 3D modeling process.** The problems of segmentation for urban scenes are inevitable due to the complexities of the selection of appropriate segmentation algorithms and their parameters. The top-down knowledge-based segmentation methods (Boochs, 2011; Hmida, 2012a; Hmida, 2012b) and bottom-up segmentation method (such as region growing segmentation (Jagannathan, 2007; Rabbani, 2006), model fitting segmentation (Fischler, 1981; Schnabel, 2007)) and machine learning algorithms (Brodu, 2012; Lu, 2016), do not solve the segmentation of objects with complex geometric shapes at the component level.
- **Problems with the definition and extraction of topological relations among object components from point clouds and problems related to the formalized representation of topological relations.** The existing methods for describing spatial topological relations including RCC, 4IM, DE-9IM, and RCC-3D(Albath, 2010b), cannot represent adequately the topological relations between components of a complex object represented by the 3D B-Rep model.
- **The complexity of the semantic labeling of objects in urban scenes at object components level as well as at the object level (the problems of inferring high-level semantic information of objects, such as building roof shapes and architecture style).** Research on knowledge-based solutions for semantic labeling has partly solved the knowledge representation using ontology and semantic rules. However, designing a knowledge base containing formalized topological relations between object components is still necessary to improve automatic semantic labeling at both the object component and the object levels. Although some efforts have been made on automatic feature recognition from point clouds, knowledge-based solutions are possible to be improved by integrating prior knowledge about objects and uncertain reasoning for semantic labeling of objects from uncertain information extracted from point clouds.
- **The absence of knowledge about objects in the creation of complete geometric 3D models from incomplete point clouds.** Based on the segmentation, the geometric properties of segments can be extracted. However, incomplete point clouds lead to problems such as shape extraction and creating

complete geometric models. After the feature recognition step, objects and their components have been recognized. The semantic information of these objects and the knowledge about their geometric properties and topological relations are crucial to create a complete 3D model of an object.

3 Hypotheses and Research Objectives

General Hypothesis

In this research, we make the assumption that the integration of qualitative information with geometric information can help to improve automatic 3D modeling of a complex urban scene from LiDAR point clouds.

Global Objective

The global objective of this research work is to improve automatic 3D modeling of a complex 3D urban scene from LiDAR point clouds by integrating qualitative information into the modeling processes. This work aims at reducing the time of the modeling process, improving the quality of the 3D geometric models, building more complete 3D models and realizing automatic feature recognition.

Specific Objectives

To achieve the global objective of this thesis, the following specific objectives have been defined:

- To propose a conceptual framework for the automatic segmentation of urban scenes by the integration of machine learning algorithms, which allows for automatic selection of segmentation algorithms and parameters for specific types of objects and the improvement of the quality of the segmentation.
- To propose a method for extraction and formal representation of topological relations between object components from point clouds.
- To propose a knowledge-based solution for automatic feature recognition from point clouds based on semantic reasoning using the formalized knowledge about objects stored in the knowledge base. In addition, to propose a rule-based solution for automatic feature recognition that can deal with uncertain reasoning based on segmentation results with uncertainties.
- To propose an approach to complete the missing parts of building components based on knowledge about buildings. We propose to develop and implement an algorithm for completing geometric building models in LOD2 and test it with the help of qualitative knowledge of buildings and their components.

4 Overview of Research Methodology

To achieve the objectives of the proposed research, the methodology will consist of four phases. These include the literature review, definition of the conceptual framework, algorithm design and prototype implementation and finally the assessment of the quality of the 3D modeling process. In the following sections, these phases are presented in more detail (Figure II).

Phase 1: Literature Review and Data Preparation

In the literature review, the motivations and significance of 3D modeling for urban areas are surveyed. The previous developments related to 3D modeling as well as their limitations, especially for automatic 3D modeling of urban scenes, are illustrated briefly. This step serves to better understand the key challenges regarding automatic 3D modeling. Understanding LiDAR technology and the observation of the environment with such technology is fundamental for this project. Furthermore, in order to improve the automatic 3D modeling from LiDAR point clouds, understanding the processes of segmentation, shape extraction and a suitable evaluation method for determining completeness and accuracy of geometric 3D models is essential. The literature review is aimed at selecting appropriate methods for classification, shape extraction, 3D modeling, and automatic feature recognition. This survey allows us to identify the limitations of those methods, the algorithms for processing complex urban scenes, and the technologies for coping with incomplete and uncertain point clouds.

Another aspect for consideration is the determination of an appropriate dataset. It is necessary that the selected dataset satisfies the objectives and has enough information in the point cloud for automatic 3D modeling realization. LiDAR data on the campus of Laval University is available to support this research project and satisfy these requirements.

Phase 2: Define a Conceptual Framework for Automatic Modeling from LiDAR point clouds

Here, the components required for designing a conceptual framework are identified. According to common methods employed to solve these complex problems, the decomposition of modeling steps can help focus on specific and key problems. For automatic modeling, several problems need to be solved, including pointwise semantic segmentation, CAD-like segmentation, shape extraction, topology extraction, and feature recognition. For the whole process, we consider automating the 3D modeling process from LiDAR point clouds by integrating geometric and semantic information on the objects and their components (Figure III).

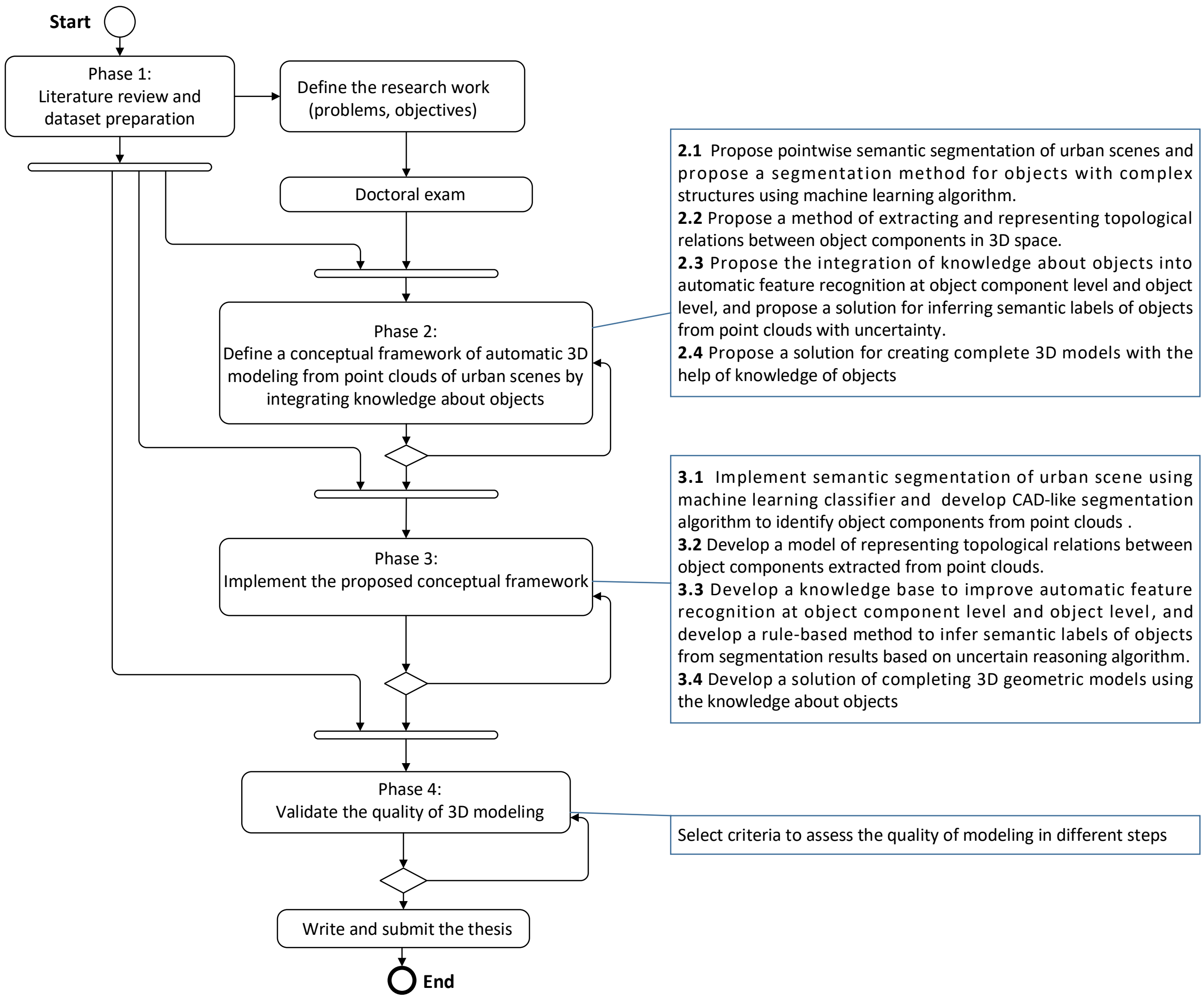


Figure II Schema of the research methodology

The pointwise semantic segmentation stage helps to determine which kinds of objects to be found in the raw point clouds. The CAD-like segmentation stage identifies the geometric shapes of object components. At this stage, the knowledge of objects will be partially extracted from point clouds, such as the surface type of objects (planar and curved), the geometric properties of object components (area, width, height, and length) and the geometric relations between them (vertical, parallel and coplanar). Topology extraction identifies the topological relations between the object components. The geometric shapes of components are extracted from the segmentation results of objects. Following this, the information extracted from point clouds must be added to a knowledge base in order to infer further semantic information concerning the objects. The feature recognition step recognizes the semantic information of buildings (such as the wall, roof, window, floor) based on the geometric information, the identified topological relations and knowledge about objects formalized in the knowledge base. This knowledge is used to improve the 3D representation of individual objects as well as the 3D scene. For realizing the goal of improving geometric models based on the knowledge of objects, there are several crucial components that must be included in our proposed framework:

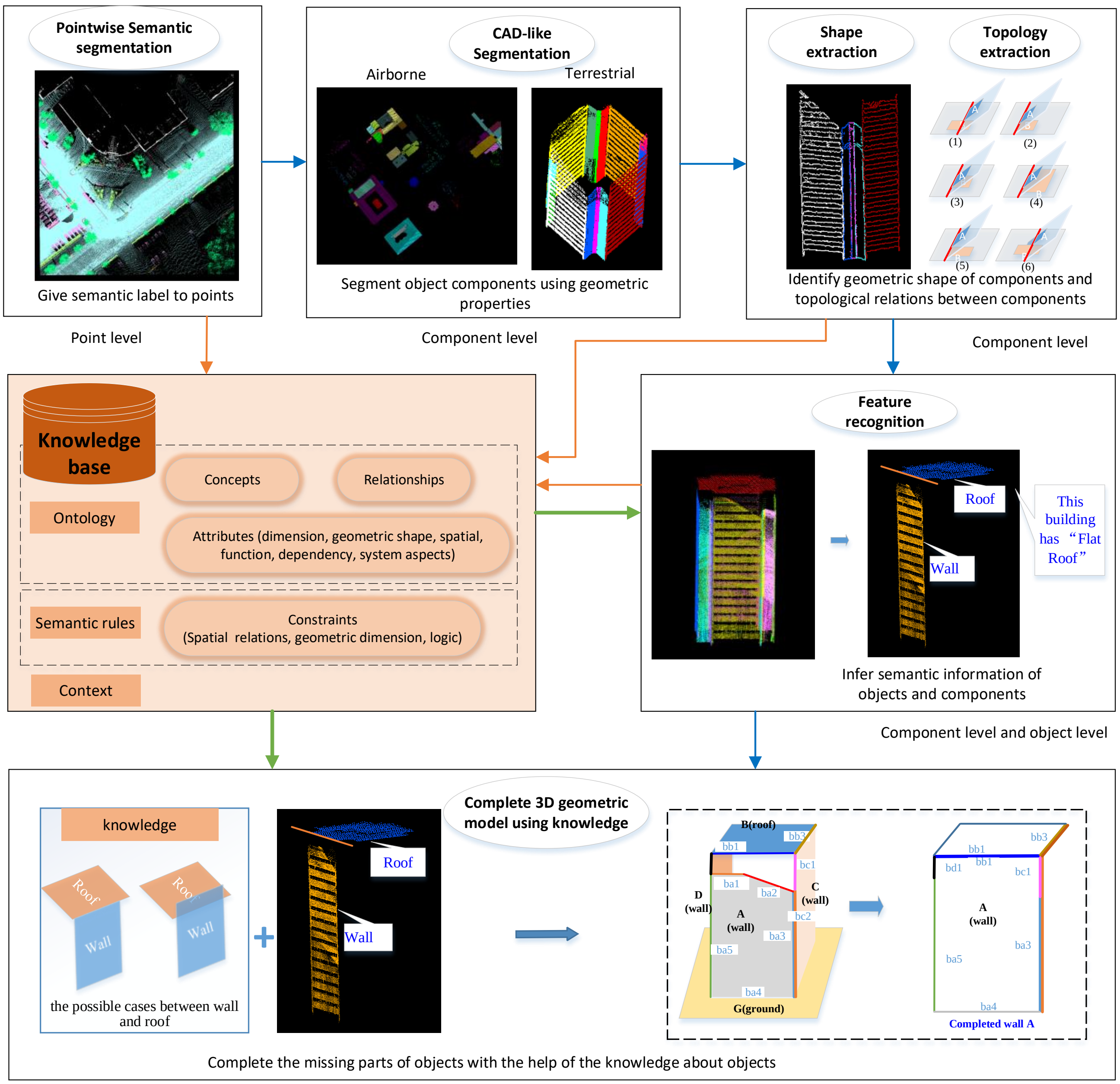


Figure III Proposed framework for automatic 3D modeling from point clouds

- The formalized representation of knowledge about objects in urban scenes consisting of quantitative and qualitative information;
- The inference of the semantic information of objects from the segmented geometric features that may include uncertainty;
- The proposal of a method for completing geometric models with the help of semantic information.

For this second phase, the expected results are as follows:

- Definition of a conceptual framework proposing a knowledge-based approach for automatic 3D modeling from point clouds;
- Construction of a prototype that integrates knowledge and machine learning based on open source libraries;
- Validation of the feasibility of this framework on the dataset acquired from an urban scene.

Phase 3: Implementation and validation of the proposed solutions

To implement the proposed conceptual framework, several key steps are as follows:

- Develop an automatic segmentation method for segmenting objects with complex structures by integrating a machine learning algorithm for the recognition of a surface type. Knowing a surface type is crucial to select the appropriate segmentation algorithms for specific types of objects and the definition of parameters. Hence, the method could be used to improve the quality of segmentation results and deal with under-segmentation, as well as the over-segmentation of point clouds with non-uniform point density.
- Create a knowledge base comprised of ontology and semantic rules for the formalized representation of knowledge about objects in urban scenes. The formalized representations of geometric properties of individual components, as well as their geometric and topological relations, are necessary for semantic reasoning. Based on this knowledge base, some semantic rules will be defined to infer higher-level semantic information about the objects (e.g., identifying building roof shapes styles).
- Develop a knowledge-based solution for the recognition of object components based on the segmentation results with uncertainties. Due to the uncertainties coming from the process of CAD-like segmentation, the geometric properties, geometric relations and topological relations extracted from segmentation results could be uncertain as well. For this purpose, several algorithms are proposed:
    - Identifying the boundaries of object components;
    - Determining the topological relations between object components;

    - Inferring semantic information on objects from uncertain information.
- Develop an approach to complete the missing parts of object components. In this step, possible connections between object components will be inferred according to predefined knowledge about the common geometric and topological constraints between object components. Following this, the missing parts will be completed with the help of crucial geometric features of objects, for example, the corners of buildings.

Phase 4: Assessments of the Quality of the Modeling

The results of the 3D modeling steps need to be evaluated during the entire process. The assessment is decomposed into several stages following the steps described in the proposed framework.

- The quality of a point cloud depends on different aspects related to its resolution and its precision (Oude Elberink, 2011). For geometric modeling, the density of a point cloud is among significant properties, which impacts directly on whether an object can be detected and whether the details of objects can be reconstructed. The number of points per square meter (pts/m^2) displayed in a histogram or a density image may be employed to evaluate the variation in density (Oude Elberink, 2011).
- The quality of segmentation can be evaluated by the recall (the surface segmentation rate), the precision (the correctness of the segmented surface) and the F-score (that indicates the overall accuracy). We use this method to evaluate the quality in the step of feature recognition as well.
- The evaluation of geometric relations relies on the statistical approach (Heuel, 2004). This will be presented and discussed in chapter 1 of this thesis in more detail.

5 Organization of the Thesis

This thesis is written with the inclusion of several articles published or submitted either in international peer-reviewed journals or at international conferences. It should be noted that some articles may contain redundancies in literature review sections. These redundancies are inevitable due to the fact that these articles are parts of the same research project. It also allows us to recall the foundation of the research in each section and to make sure of its consistency and connection helping the readers in understanding of the presented work throughout the thesis.

This introduction presents the context of this research and its motivations. It allows the reader to understand the research problem, objectives and the overall methodology as well as the expected results.

In the first chapter, the background and the knowledge related to 3D modeling are introduced, including an overview of LiDAR technology, state-of-the-art research on the classification, object detection, segmentation, topological models, feature recognition and complete 3D geometric models creation from point clouds of urban scenes. This chapter introduces the methods and technologies for knowledge representation and solutions for dealing with uncertain information as well.

In the second chapter, an improved pointwise semantic segmentation method for airborne and mobile terrestrial LiDAR point clouds is presented based on the new proposed features including difference of normal, directional height difference and other features derived from normal estimation.

The third chapter presents a CAD-like segmentation of complex buildings from urban scenes through integrating machine learning classifiers that classify surface types. Based on the classified surface types, the automatic selections of segmentation algorithms and their parameters are carried out. This method can deal with under-segmentation and over-segmentation of objects with complex structures.

The fourth chapter presents an approach for the definition and extraction of topological relations between the components of a 3D object represented by B-Rep models from point clouds. This chapter relates to a paper published in The International Archives of the International Society of Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS).

The fifth chapter presents a knowledge-based automatic feature recognition from point clouds acquired in an urban scene. The knowledge base consists of ontology containing several modules that describe an urban scene from different perspectives, properties, relations, constraints, and semantic rules. Instances and relations identified from the segmentation results of an urban scene are considered as facts and added into the knowledge base. Then, semantic information of objects and their components are inferred based on the knowledge. Several experiments showed that our approach is capable of reasoning semantic information from incomplete point clouds in some cases. The chapter relates to a paper published in the ISPRS International Journal of Geo-Information.

In the sixth chapter, our solution for automatic feature recognition from the segmentation results with uncertainties is presented. Object components are recognized from uncertain geometric properties of segments with support of the knowledge base as well as the geometric and topological relations extracted from point clouds. The Dempster-Shafer evidence theory is chosen to infer the semantics of objects based on the uncertain information on the objects.

The seventh chapter presents the implementation of the proposed method for creating a complete 3D geometric model with the help of the knowledge about the object components. Experiments are conducted on the creation of a complete 3D geometric model of buildings from incomplete point clouds.

The conclusion section presents an overview of the thesis, and the achievement of the different objectives, the original contributions of the proposed research work with a discussion related to its strengths and weaknesses, and some perspectives for future work.

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CHAPTER 1 Background

1.1 Introduction

Chapter 1 summarizes the research presented in this thesis based on several notions that support automatic 3D modeling of an urban environment. We first present the fundamentals and characteristics of LiDAR technologies, as well as the modeling methods derived from point clouds. In the second section, we explore the state-of-the-art process of automatic 3D modeling, including the crucial steps and complexities involved. We discuss the roles of classification, object detection, segmentation, topology, and feature recognition in creating complete 3D geometric models using an automatic approach, and describe the role semantics and knowledge play in these steps. In the third section, elements of knowledge representation and reasoning are presented. Lastly, we present and discuss the methods of uncertain reasoning used in automatic 3D modeling.

1.2 Background on 3D Modeling of LiDAR Point Clouds

1.2.1 Introduction to LiDAR technologies

LiDAR, which stands for "Light Detection And Ranging," first appeared in a few publications in the 1980s (NOAA). Although often referred to as "3D laser scanning," LiDAR is an emerging 3D data acquisition technology that employs a laser and a rotating mirror to rapidly scan volume and surface areas such as rock slopes and outcrops, buildings, bridges, and other natural and man-made objects (Kemeny, 2008). In terms of specific purposes, LiDAR devices are generally classified into two categories: terrestrial LiDAR and airborne LiDAR, depending on the platforms upon which the devices are mounted. Airborne LiDAR has three basic data collection components: a laser scanner, a global positioning system (GPS) receiver and an inertial measuring unit (IMU). With airborne LiDAR, a laser beam is sent to the ground and the LiDAR device receives the reflected signal. The device records the amount of time it takes for the laser signal to return to the device. The signal travels the distance from the airborne platform to the ground twice. The IMU records the angle at which the laser beam signal is sent out, while the GPS receiver determines the 3D position of the LiDAR device. Using geometry principles, the elevation value of a detected point can be calculated. Mobile terrestrial LiDAR works the same way as a static terrestrial LiDAR, which uses a 3D laser scanner installed on a tripod to collect a 3D point cloud of the surrounding environment (Shan, 2009).

Table 1-1 A comparison of LiDAR systems

Type of LiDAR	Platform	Parameter	Range of application	Advantage	Shortage
Terrestrial LiDAR	Fixed position or mobile vehicle	(1) Pulse Repetition Rate (PRR): 2KHZ~25KHZ (2) GPS positioning (3) Inertial measurement	To build terrain models, exterior street view building models	(1) With mobile LiDAR, the observation range is flexible, (2) With static LiDAR, there is a high level of precision.	With static LiDAR (1) Multiple scans from different positions are required, (2)A small portion of the data under the observation location will be missing.
Airborne LiDAR	Airplane or helicopter	(1) GPS positioning (2) Density: Ranges from 1 point/20 m^2 to 20 points/m^2 at a height of 1000 m, but depends on PRR, flight speed, scan angle, and aircraft altitude (3) Accuracy (Yan, 2007): 15 cm (vertical), 1.5 times vertical(horizontal)	(1)To obtain roof structures of buildings (2)To determine terrain models	(1) To obtain large-scale area point clouds in a short time (2) To obtain vertical profiles from the air	(1) The density of point clouds is less than that of terrestrial LiDAR (2) Provides the terrain information, but must distinguish between buildings and vegetation
Indoor LiDAR	Indoor fixed position or mobile (manual or robotic) platform	(1) Limits the size of LiDAR devices and platforms; (2) Other parameters are similar to those used with terrestrial LiDAR	To view the inner structure of buildings and create interior 3D models	(1) To obtain the high-density point clouds of building interiors, (2) Best for viewing small spaces	(1) Terrestrial point clouds need to be combined for building modeling (2) Provides room information but the view of interior structures can be easily obstructed

Airborne LiDAR has been used as an interesting data source for digital terrain modeling for engineering projects, disaster management, as well as visualization tasks. Mobile terrestrial LiDAR and airborne LiDAR can be used for outdoor data acquisition. Table 1-1 introduces and compares different types of contemporary LiDAR technologies. (Mostafavi, 2011) carried out a survey of LiDAR technologies and modeling software. The results of that survey suggest that these techniques can be used efficiently to monitor new construction and facilitate the management of industrial plants through rapid data acquisition and modeling processes. However, given the mobility, size and nature of the platforms, LiDAR devices designed to be mounted on land vehicles seem to be most suitable for measuring building exteriors. Different systems can be used inside buildings, such as the Trimble Indoor Mobile Mapping Solution (TIMMS), the GeoSLAM Zeb Horizon system, and the Faro Focus 3D Laser Scanner. Figure 1-1 illustrates the three types of acquisition systems.

A B C

Figure 1-1 (A) TIMMS system; (B) GeoSLAM Zeb Horizon system; (C) FARO Focus 3D laser scanner

1.2.2 Selecting a Data Source for 3D Modeling

Selecting an appropriate 3D data source is the first step in 3D urban environment modeling. Today's LiDAR scanners can collect more than a million points per second (1 MHZ). The Leica HDS6000 scanner can collect 500,000 points/sec. State-of-the-art phase-based scanners such as the Faro LS120 can collect measurements up to a distance of 120 meters at a rate of 1,000,000 points/second (Harrap, 2010). The recent Faro Focus series, which collects up to 976,000 points/sec, is equipped with a High Dynamic Range (HDR) photo recording function used to produce coloured point clouds. Its measurement range can reach up to 350 meters. The Leica ScanStation P30/P40 has a pulse rate of up to 1 million points/second and a measurement range of up to 270 meters. The P50 version has the same scan rate but a much longer measurement range, reaching as far as 1000 meters (Leica, 2019). In contrast, collecting data at this level of detail through traditional surveying methods would take much more time (Harrap, 2010). The precision of acquired data is also a significant criterion. LiDAR data is extremely precise and can provide measurements with the precision of a few millimeters (mm). Therefore, LiDAR data is a very good choice for creating detailed 3D models in terms of acquisition speed, density and precision. Point clouds extracted from stereo images also represent an alternative source of data. This technology is indeed less expensive but the point clouds produced may also not be as accurate. However, it is becoming a popular tool for building less accurate 3D city models. Thus, compared to the points extracted from stereo images, LiDAR data can result in more accurate and detailed 3D models. The advantages of point clouds produced from LiDAR are unparalleled in terms of high-accuracy, high-density and high-speed data acquisition for the reconstruction of urban area 3D models.

3D city modeling is one of the most interesting applications that benefit from point clouds derived from LiDAR technology. For 3D city models, LiDAR data provides accurate elevation and surface information that can be used to distinguish various types of objects, such as buildings and vegetation. Airborne LiDAR is a good choice for 3D modeling of large-scale urban areas in terms of range, accuracy and speed of data acquisition, while ground-based mobile LiDAR is better for capturing detailed street-level information. However, airborne LiDAR data may not be dense enough for certain 3D modeling tasks because measurement density depends on the LiDAR data collection rate, which, in turn, is affected by the altitude and ground speed of the aircraft (Corporation, 2002; Crawford, 2018; Harrap, 2010). A combination of airborne and ground-based mobile LiDAR therefore provides a better solution in order to fully cover an urban area and capture enough detailed information for 3D modeling purposes.

1.3 Cutting-edge Automatic 3D Modeling from LiDAR Point Clouds

1.3.1 Classification of point clouds

The classification of LiDAR point clouds is an important step when creating 3D models. Classification involves grouping points that belong to specific types of objects into the same class. There are two widely accepted strategies for classifying point clouds: 1) separating the ground, trees, and buildings, and 2) moving objects from the point cloud simultaneously. Similar characteristics extracted from the point clouds determine which points should be grouped together. Filin (Filin, 2002b) presents a point clustering algorithm for extracting homogeneous segments from airborne laser data. The algorithm is not limited to specific geometric shapes because the aim of clustering is to group the data into homogeneous patterns without establishing a clear definition for the patterns beforehand. Brodu (Brodu, 2012) presents a method for classifying point clouds of natural scenes using multi-scale, local dimensionality criteria for each point. Here the scale is defined as the diameter of a ball centered on a point of interest. This method is insensitive to shadow effects, and can involve classification of point clouds with missing data. This method has been implemented in CloudCompare as a plug-in, allowing users to define and create classes.

Another method for classifying points is to separate them into ground and non-ground measurements from point clouds first, and then identify subclasses based on ground and non-ground points: buildings, trees and other objects from non-ground points, and roads, lawns and bare earth from ground points. Height and intensity information represent basic information in point clouds and can be used to classify points (e.g., separating the ground points from the non-ground points using a skewness balancing method that is based on the assumption that ground point altitude is normally distributed while non-ground points disrupt this normal distribution (Arefi, 2003; Bartels, 2010; Yunfei, 2008), employing a slope-based filter to identify ground points (Vosselman, 2000) and/or using a morphological filter to remove non-ground measurements from airborne LiDAR data (Zhang, 2003). If necessary, the classification details can be refined following this rough classification.

1.3.2 Object Detection

The process of determining the range of the subset that belongs to every single object in the point cloud is usually called object detection (Dorninger, 2007; Wang, 2007b). Object detection identifies the object of interest from point clouds. In other words, object detection tries to find instances of the object of interest. Detecting objects (terrain, trees, cars, buildings, roads and so on) from the point cloud first requires that ground and non-ground objects be distinguished. Then, additional object detection from non-ground point clouds will distinguish the ranges of other objects (such as buildings, cars, etc.) in several steps. There are some well-known methods to identify objects. For instance, the edge-based detection method is designed for building extraction and reconstruction based on their geometry and shapes, including orthogonality, parallelism, circularity, and symmetry (Wang, 2000). Object detection methods for specific types of objects are presented as follows:

- **Footprint detection.** Geometric properties such as height, shape, and size are used to distinguish buildings and generate the outline of a building from airborne LiDAR data. Several steps are needed to obtain the footprints of buildings. First, a digital surface model is generated and then objects higher than the ground are detected automatically (Hu, 2003). Based on the detection of buildings from non-ground measurements using a region-growing algorithm, raw footprints for building measurements are derived by connecting boundary points. Raw footprints are further simplified and adjusted to remove noise caused by irregularly spaced LiDAR measurements (Keqi, 2006). Another solution for detecting building footprints can be carried out by an Adaboost (Adaptive Boosting) machine learning algorithm to classify point clouds. Then, a Bayesian technique can be used to automatically construct the footprint from a pre-classified point cloud (Oliver, 2006).
- **Road detection.** For identifying a road inventory, (Pu, 2011) has proposed an initial rough classification of a point cloud with three categories (ground surface, objects on the ground and objects off the ground) and then the point cloud is classified based on size, shape, orientation, and topological relationships. Finally, knowledge-based methods and shape recognition are used to detect basic structures related to road inventory from classified point clouds.

Another solution for object detection is to group points that belong to a single object from raw point clouds by similarities, such as spatial distance, height, and surface characteristics (planarity, smoothness, and orientation). This solution is similar to the unsupervised clustering algorithm. The similarity among points decides the results of object detection. The advantage of this solution is that the algorithm design is unified and parameter selection has the same criterion. However, the computation cost and the accuracy of object detection still need to be improved.

For identifying man-made objects (buildings, roads) from point clouds, geometry, shapes, size, surface characteristics and spatial relations are crucial information. The knowledge chosen for object detection may vary with respect to different methods of data acquisition. For example, the attribute “return number” is effective in classifying vegetation, ground, and building from airborne LiDAR but not from mobile terrestrial LiDAR scanners. Therefore, with object detection, prior knowledge about the objects of interest is crucial in designing methods for detecting a single object from point clouds.

In summary, object detection plays a vital role in finding the range of a single object of interest and reducing the computation cost during 3D modeling of point clouds. However, the creation of 3D models of objects requires detailed geometric information of the object and its components. Object detection is still a rough classification because it provides limited spatial and semantic information of objects and their components, such as the geometric properties and shapes of objects, types, spatial relations and topological relations to other objects. More importantly, the semantic labels of objects are difficult to extract directly from point clouds. Therefore, for 3D modeling of a complex urban scene, the segmentation of point clouds according to similar attributes will produce more detailed information.

1.3.3 Segmentation

The aim of segmentation for a single object is to partition a data set into simpler groups that represent the components of an object, to decrease the search space range, to reduce the computational cost and to simplify or change the representation into something that is more meaningful and easier to analyze (Shapiro, 2001). Segmentation (Dorninger, 2007) involves aggregating points that have similar attributes or meaning into a common segment representing the parts of an object. In this step, points are classified into different segments according to diverse criteria. Geometric properties are very helpful for the segmentation of a point cloud from man-made objects in an urban area because these objects are mostly composed of regular shapes (Jochem, 2009). In such a context, detecting geometric primitives (rectangles, circles, and polygons on planes, cylinders, spheres, cones, etc.) is fundamental for the segmentation of a point cloud. The segmentation based on local features is usually the preferred method. Due to the fact that the neighboring points have closer relationships (Tobler, 1970), those points on a surface or belong to an object having similar properties. Segmentation of a point cloud can be based on additional data sources such as 2D images (Liu, 2012; Marshall, 2001) and the results can be used for 3D modeling (Awwad, 2010; Barnea, 2013a;

Li, 2011; Ning, 2009; Pu, 2006a; Pu, 2007; Schnabel, 2007). Segmentation algorithms can be divided into the following categories:

1.3.3.1 Edge-based method

Edge-based segmentation algorithms contain two main stages (Rabbani, 2006): edge detection, which outlines the borders of different regions, and the grouping of points inside the boundaries providing the final segments. Edges can be defined as the set of points whose local surface properties (e.g., normal) have rapid changes. The most commonly used local surface properties include surface normal, gradients, principal curvatures, or higher-order derivatives. Some typical variations of the edge-based segmentation techniques are reported in the segmentation of depth images (Bhanu, 1986) and 3D point clouds (Castillo, 2013; Sappa, 2001). This kind of method allows for fast segmentation. However, the accuracy of results is sensitive to data quality (noisy and uneven density of point clouds).

1.3.3.2 Scanline-based method

Scanline segmentation methods depend on scan line information for extracting man-made features. (Manandhar, 2001) classified airborne point clouds into buildings and roads according to the direction (vertical or horizontal) of the scan lines. However, it is very difficult to extract natural objects using these methods since point clouds of natural objects (for example, trees) are scattered points without any apparent line features. (Abuhadrous, 2004) processed each profile and classified points as a vertical façade, a horizontal road, and trees according to elevation Z and Y direction. (Sithole, 2003) employed the same scan line principle for detecting urban structures and merged segments if they shared one or more points. In summary, scanline segmentation methods only can detect line features from point clouds.

1.3.3.3 Region-growing methods

Region-growing methods are generally used to segment point clouds containing many planar structures for the process of 3D modeling of urban areas. Neighborhood information of selected points is used to detect the region where points have similar properties. The region-growing method can be classified into seeded-region and unseeded-region methods (Nguyen, 2013).

Seeded-region methods: Seeded-region methods grow regions from a number of seed points, and then the neighbor points satisfying specific criteria or a defined threshold are added to regions. Pu et al. (Pu) presented a building facade extraction method of 3D modeling from terrestrial LiDAR data. This method uses a surface growing strategy to extract planes (Vosselman, 2004) based on TINs (Triangulated Irregular

Network) and the evaluation of the surface normal vector. However, the results show that over-segmentation can occur. A planar region-growing algorithm is proposed to segment the plane and then extract facades automatically based on knowledge of buildings and several kinds of common and important building components (Pu, 2006b). A segmentation method for point clouds via an octree structure is proposed based on a split-and-merge approach, coherence, and proximity of point clouds (Wang, 2011). The segmentation of planar regions (Rusu, 2011; Rusu, 2008b; Rusu, 2009b) is developed based on the smoothness constraints as described in (Rabbani, 2006). In summary, the seeded-region methods are closely dependent on the selection of seed points. The seed point determines growing processing. Seeded region-growing methods are quick ways to extract planar surfaces but they are sensitive to noisy data. In addition, these methods cannot be used to segment point clouds incorporating a variety of geometric shapes for shape-based segmentation, especially with noisy data.

Unseeded-region methods: The central principle of unseeded-region methods is to divide one region into smaller regions according to predefined criteria. For example, this method is used to cluster planar regions to reconstruct the complete geometry of architectural buildings based on the confidence rate of the local area to be planar (Chen, 2008). The limitation of these methods is that they may produce over-segmentation and only perform well for the segmentation of objects with planar surfaces. Another limitation is that this method requires a large amount of prior knowledge which is usually limited in complex scenes.

1.3.3.4 Model Fitting Methods

The model fitting method is based on matching geometric primitive shapes. If geometric shapes can be represented mathematically as planar surfaces and other geometric shapes, those points that match the mathematical representation would be grouped as one segment. There are two methods for model fitting: RANdom SAmple Consensus (RANSAC) and 3D Hough transform. Generally, for automatic detection of planes from point clouds, RANSAC is more efficient in both segmentation results and running time. 3D Hough transform is more sensitive to the segmentation parameter and the running time is longer (Tarsha-Kurdi, 2007b). Indeed, RANSAC (Fischler, 1981) is commonly used because it has the great advantage of being robust, even in the presence of significant noise in the data set. For example, Schnabel et al. (Schnabel, 2007) provided an efficient RANSAC algorithm to extract basic geometric shapes, including planes, spheres, cylinders, cones, and tori. The experiment showed that the algorithm is robust even in the presence of high noise and numerous outliers. Nevertheless, there are also shortcomings that should not be overlooked, such as spurious planes produced from point clouds acquired from stair structures (Awwad, 2010). An extended "SEQ-NV_RANSAC" approach (Awwad, 2009) and an improved RANSAC method based on normal distribution transformation cells for plane segmentation (Li, 2017) were developed to avoid under-segmentation and over-segmentation. In the Point Cloud Library (Rusu, 2011), several extensions are available to set the parameters in RANSAC, including MLESAC (Maximum Likelihood Estimation SAmple and Consensus), MSAC (M-estimator SAmple and Consensus), and PROSAC (Progressive Sample and Consensus).

The combination of the RANSAC algorithm and the region-growing method is a feasible solution for decreasing segmentation problems because the region-growing method can detect the coarse segmentation and RANSAC algorithm is robust for noisy data. For instance, Chen et al. (Chen, 2012) introduced a progressive morphological filter technique to distinguish the ground and non-ground information and then used a region-growing method and adaptive RANSAC based on the grid structure to improve the selection efficiency of uncertain local sampling points. Information on distance, standard deviation, and normal vectors were used to keep the topology complete. The method proposed in (Cheng, 2013) is that a coarse segmentation is created using TINs (Triangulated Irregular Network) and the angle between two adjacent triangles as an aggregation criterion (45 is threshold), and then the local triangle cluster and local fitting RANSAC together are used to find the best plane according to a given threshold. Chen et al. (Chen, 2014) has proposed an improved RANSAC segmentation algorithm to segment the rooftop primitives through the localized sampling and then a region-growing-based triangulated irregular network (TIN) is applied to separate the coplanar primitives. This kind of solution is less sensitive to noise, and it can avoid over- and under-segmentation of building primitives. In summary, model fitting methods are fast and robust in detecting geometric primitives even from point clouds with outliers. Model fitting methods are efficient in detecting geometrically simple parameterized shapes. However, they have shortcomings in detecting complex shapes or fully automated implementations.

In 3D city modeling, most of the object components are represented by geometric primitives. Some details cannot always be modeled into recognizable geometrical primitives in the architectural field. Thus, model fitting methods are effective for segmenting objects with regular geometric shapes and if possible, color content (Barnea, 2013b) and for distinguishing segments from geometric properties.

1.3.3.5 Clustering-based methods

The clustering method, which relies on the analysis of a feature, data clustering and grouping, offers a basic way to identify homogeneous patterns in the data but does not restrict to one specific pattern. The feature can be directly extracted from point clouds based on the clustering method, especially in the presence of noisy data and outliers. However, the computation of multidimensional clustering features for mass data is costly. For example, a vector for each point representing its features contains the point coordinates, the surface normal for this point, and the relative height difference between this point and its neighbors. The feature vector for each point is then used in the clustering algorithm (Awwad, 2010). A novel hierarchical clustering algorithm named Pairwise Linkage (P-Linkage) was designed to segment unstructured point clouds. Then a feature value was calculated for each data point, for example, the density of 2D data points and the flatness for 3D point clouds. After merging clusters, the final segmentation results were obtained (Lu, 2016). In summary, this method is sensitive to the definition of the distance between neighborhoods and noisy data. Therefore, it is less effective in the segmentation of a point cloud from complex urban areas.

In conclusion, although some algorithms have proven to be effective for the segmentation of point clouds, the parameters still need to be adjusted for different qualities of the point cloud. In addition, selecting a segmentation strategy is not easy because over-segmentation and under-segmentation may occur if the right strategy is not adapted to the context and data quality. Essentially, the segmentation and surface fitting can be regarded as the “chicken and egg” problem (Awwad, 2010; Várady, 1997). If a priori information about the surfaces is available, we can design the appropriate algorithms with appropriate parameters to extract the surface. Therefore, for the segmentation of complex urban scenes, the quality of segmentation can be improved if the prior knowledge about the specific types of objects is known.

1.3.3.6 Segmentation and fusion with images

Combining LiDAR data and images is an approach based on a new Shrink-Expand strategy (Cheng, 2013), which combines LiDAR data and optical aerial imagery and completes the construction of 3D models by incorporating segmented roof points and 2D lines extracted from optical multi-view aerial images. Other examples include the segmentation of point clouds by fusing spin images and ground-based LiDAR (Caceres, 2007), the fusion of high-resolution optical images with LiDAR data for improving image segmentation results (Awad, 2017), and the fusion of LiDAR and hyperspectral datasets for the semantic segmentation of hyperspectral images (Aytaylan, 2016).

1.3.4 Topology

Topology is fundamental to creating the necessary connections between objects and object components. When object components are segmented from point clouds, identifying the topology among object components makes it possible to assemble object components as a topological 3D geometric model of an object. Spatial relations such as topological, distance and directional relations, are among the semantic information for describing a scene (Mark, 1994). Topological relations are used to represent spatial relations between geographical objects and are necessary for spatial analysis, spatial query and data structure design in GIS. Spatial relations between objects are queried and analyzed regardless of geographic coordinate systems and the accurate position of objects. The concern with topological relations is how to define the spatial relations between two objects. Topological relations are invariant with respect to affine transformations, such as translation, scaling, and rotation (Egenhofer, 1990b). For 3D modeling from point clouds, topological relations between objects and their components are important information to extract for semantic description and representation of objects.

Topological relations between objects can be derived from Region Connection Calculus (RCC) (Egenhofer, 1989; Egenhofer, 1991b) in R^2. The 4-Intersection Model (4IM) (Egenhofer, 1991b), 9-Intersection Model (9IM) (Clementini, 1993) and Dimensionally Extended 9-Intersection Model (DE-9IM) (Clementini, 1993) are widely adopted and implemented for spatial analysis. In 3D space, according to specific applications, an appropriate topological model is used. For 3D modeling from point clouds, creating 3D models from basic geometric primitives require topological relations among primitives for connecting objects components and subsequent analysis (Pigot, 1991). However, 2D topological models need to be extended to 3D space for the analysis of relations among 3D objects. For instance, RCC-3D (Albath, 2010b) and VRCC-3D+ (Albath, 2010b; Sabharwal, 2011) were developed based on RCC for the analysis of the topological relations between objects in 3D space. However, to define topological relations between 3D object components, existing topological models cannot meet the requirements of topological relations analysis between the components of a single object represented by Boundary Representation (B-Rep) models because RCC is defined based on the relation between 2D region and RCC-3D extends RCC in 3D based on the projection of 3D objects in specific planes for determining the topological relations between 3D objects. Therefore, a formalized representation and a discrimination method for the topological relations between object components are indispensable in 3D modeling and spatial analysis from point clouds.

1.3.4.1 Topology in 2D

1.3.4.1.1 Calculus-based spatial logic model

Region Connection Calculus (RCC) (Egenhofer, 1989; Egenhofer, 1991b) is the basis of the definition of topological relationships in 2D space. Topological relationships are grouped into six types: point-point, point-line, point-region, line-line, line-region, region-region relations. Among them, the spatial relations between regions are used to describe topological relations as compared with other types, topological region-region relations are most commonly used (Deng, 2007) in the spatial analysis in R^2. Eight topological relations defined by (RCC-8) are as follows(Randell, 1992): disconnected (DC), partial overlap (PO), equal (EQ), externally connected (EC), tangential proper part (TPP), non-tangential proper part (NTPP) and their inverse relations TPPi and NTPPi respectively, where P is part relation and PP is proper part relation, C means connection and O indicates overlap. The formalized definitions of these topological relations are presented as follows (Randell, 1992) :

$$DC(x,y) \equiv \neg C(x,y)$$

$$P(x,y) \equiv \forall z[C(z,x) \rightarrow C(z,y)]$$

$$\mathrm{PP}(x,y) \equiv P(x,y) \wedge \neg P(y,x)$$

$$x = y \equiv P(x,y) \wedge P(y,x)$$

$$O(x,y) \equiv \exists z[P(z,x) \wedge P(z,y)]$$

$$PO(x,y) \equiv O(x,y) \wedge \neg P(x,y) \wedge \neg P(y,x)$$

$$EC(x,y) \equiv C(x,y) \wedge \neg O(x,y)$$

$$TPP(x,y) \equiv PP(x,y) \wedge \exists z[EC(z,x) \wedge EC(z,y)]$$

$$NTPP(x,y) \equiv PP(x,y) \wedge \neg \exists z[EC(z,x) \wedge EC(z,y)]$$

1.3.4.1.2 4-Intersection Model

In the "4-Intersection" Model (4IM) (Egenhofer, 1989; Egenhofer, 1991b), eight topological relationships are defined. The relations in 4IM are: disjoint, meet, overlap, contain, cover, coveredBy, containedBy and equal. They correspond to RCC-8 relations DC, EC, PO, NTPP, TPP, TPPi, NTPPi, EQ, respectively. They are defined on the basis of the intersection relations of the boundary (∂A) and interior (A^o) of two regions. The intersection values are distinguished only by "empty" and "non-empty".

$$T(A,B) = \begin{bmatrix} A^\circ \cap B^\circ & A^\circ \cap \partial B \\ \partial A \cap B^\circ & \partial A \cap \partial B \end{bmatrix} \qquad \textbf{(Eq 1-1)}$$

$$\text{disjoint(A,B)} = \begin{bmatrix} \varnothing & \varnothing \\ \varnothing & \varnothing \end{bmatrix} \quad \text{meet(A,B)} = \begin{bmatrix} \varnothing & \varnothing \\ \varnothing & \neg\varnothing \end{bmatrix} \quad \text{overlap(A,B)} = \begin{bmatrix} \neg\varnothing & \neg\varnothing \\ \neg\varnothing & \neg\varnothing \end{bmatrix}$$

$$\text{cover(A,B)} = \begin{bmatrix} \neg\varnothing & \neg\varnothing \\ \varnothing & \neg\varnothing \end{bmatrix} \quad \text{contain(A,B)} = \begin{bmatrix} \neg\varnothing & \neg\varnothing \\ \varnothing & \varnothing \end{bmatrix} \quad \text{coverBy(A,B)} = \begin{bmatrix} \neg\varnothing & \varnothing \\ \neg\varnothing & \neg\varnothing \end{bmatrix}$$

$$\text{containedBy(A,B)} = \begin{bmatrix} \neg\varnothing & \varnothing \\ \neg\varnothing & \varnothing \end{bmatrix} \quad \text{equal(A,B)} = \begin{bmatrix} \neg\varnothing & \varnothing \\ \varnothing & \neg\varnothing \end{bmatrix}$$

1.3.4.1.3 9-Intersection Model

In the "9-Intersection" Model (9IM) (Egenhofer, 1993; Egenhofer, 1990a), as compared to 4IM, the topological relations additionally consider the exteriors of two regions. The "4-Intersection" is easily extended to the "9-Intersection" consisting of nine elements in a 3*3 matrix.

$$T(A,B)=\begin{bmatrix} A^{\circ}\cap B^{\circ} & A^{\circ}\cap\partial B & A^{\circ}\cap \mathrm{B}^{e} \\ \partial A\cap B^{\circ} & \partial A\cap\partial B & \partial A\cap \mathrm{B}^{e} \\ A^{e}\cap B^{\circ} & A^{e}\cap\partial B & A^{e}\cap \mathrm{B}^{e} \end{bmatrix} \qquad \textbf{(Eq 1-2)}$$

Where A^e is the exterior of A. The boundary of A is ∂A and the interior of A is A^o. The topological relations of "9-Intersection" are presented as follows (Clementini, 1994):

$$\text{disjoint(A,B)=}\begin{bmatrix} 0 & \delta & \delta \\ \delta & 0 & \delta \\ \delta & \delta & \delta \end{bmatrix} \quad \text{meet(A,B)=}\begin{bmatrix} 0 & \delta & \delta \\ \delta & 1 & \delta \\ \delta & \delta & \delta \end{bmatrix} \quad \text{overlap(A,B)=}\begin{bmatrix} \delta & 1 & \delta \\ 1 & \delta & \delta \\ \delta & \delta & \delta \end{bmatrix}$$

$$\text{cover(A,B)=}\begin{bmatrix} \delta & 1 & \delta \\ 0 & 1 & \delta \\ \delta & \delta & \delta \end{bmatrix} \quad \text{contain(A,B)=}\begin{bmatrix} \delta & 1 & \delta \\ \delta & 0 & \delta \\ \delta & \delta & \delta \end{bmatrix} \quad \text{coveredBy(A,B)=}\begin{bmatrix} \delta & 0 & \delta \\ 1 & 1 & \delta \\ \delta & \delta & \delta \end{bmatrix}$$

$$\text{containedBy(A,B)=}\begin{bmatrix} \delta & \delta & \delta \\ 1 & 0 & \delta \\ \delta & \delta & \delta \end{bmatrix} \quad \text{equal(A,B)=}\begin{bmatrix} \delta & \delta & \delta \\ 0 & \delta & 0 \\ \delta & \delta & \delta \end{bmatrix}$$

Where 0 and 1 represent the empty and non-empty, respectively. Each δ indicates a value of either 0 or 1. Although the exterior definition is added to the determination of topological relations, no more relations between region-region are distinguished from "9-Intersection" model (Chen, 2001).

1.3.4.1.4 The Dimension Extended Model

For the purpose of describing more detailed topological relations, a dimension extended method was presented in (Clementini, 1993). The dimensionality of the intersection is indicated by different values (-1, 0, 1 and 2). The value -1 indicates the null set. 0 indicates that intersection contains at least one point but no lines or areas. Similarly, 1 indicates that it contains at least a line and no area, and 2 indicates it contains at least an area. The Dimensionally Extended 9-Intersection Model (DE-9IM) (Strobl, 2008) provides a full descriptive for two geometries in 2D. The "9-Intersection" model belongs to binary classification. The values of elements in the typical "9-Intersection" model are only empty and non-empty. However, the corresponding elements in DE-9IM become the dim function of those elements in the "9-Intersection" model.

$$DE\text{-}9IM(A,B) = \begin{bmatrix} \dim(A^\circ \cap B^\circ) & \dim(A^\circ \cap \partial B) & \dim(A^\circ \cap B^e) \\ \dim(\partial A \cap B^\circ) & \dim(\partial A \cap \partial B) & \dim(\partial A \cap B^e) \\ \dim(A^e \cap B^\circ) & \dim(A^e \cap \partial B) & \dim(A^e \cap B^e) \end{bmatrix} \quad \textbf{(Eq 1-3)}$$

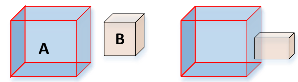
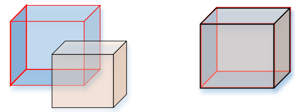
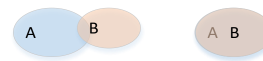
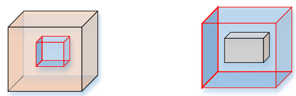
Where A^e, the exterior of A, represents everything that is not in the closure of A (denoted as $\overline{A}$). The boundary of A is ∂A and the interior of A is A^o. $dim(s) = max\{dim(s_1), dim(s_2),\ldots,dim(s_n)\}$, s is the spatial set of the intersection of the interior boundary and exterior of A and B. The value of dimension -1 means empty set, 0 for points, 1 for lines and 2 for areas. But in the query of topological relations, the 3*3 matrix is formatted as a string code. The DE-9IM code is an accepted standardized format in the OGC standards. The DE-9IM has been implemented in PostGIS for data analysis (Boundless, 2014). More importantly, it can translate geometric information into the semantic description.

1.3.4.2 Topology in 3D

Although existing RCC models have been applied in Qualitative Spatial Reasoning (QSR) in the field of robotics and GIS, medicine and engineering problems for reasoning about topological relationships (Cohn, 2008), QSR theories are primarily designed and used in R^2. In all the 512 possible relations, eight relations are recognizable in R^2. Similarly, eight relations are used for 3D objects in R^3 (Zlatanova, 2004) (Table 1-2). RCC-3D (Albath, 2010b) extends spatial reasoning to 3D based on Generalized 2D Region Connection Calculus (GRCC) (Li, 2004). Except for the same eight relations in R^2, RCC-3D introduced additional relations through the projection of 3D objects on the plane X-Y, Y-Z, and Z-X. Based on the relations of projected 2D objects in three planes, the combination of these relations can distinguish new relations between 3D objects in 3D space. Finally, this method can define 13 RCC-3D relations (Albath, 2010a). Similarly, VRCC-3D+ (Sabharwal, 2011) used RCC-3D and depth parameter to distinguish non-occlusion, partial occlusion and complete occlusion relations in 3D space, which relies on the viewpoints and the projection planes.

As mentioned, in 3D space, 3D relations are defined based on regions in R^2. In the 9-Intersection model, topological relations are determined by the intersection of the interior, boundary, and exterior of region A and region B in R^2. The basic eight relations are described by these three parts of region A and region B. RCC-3D is primarily derived from Parthood and Connectivity. For representing obscuration relations, further relations are defined by the regions A_p and B_p projected on a plane P. In summary, the definition of relations in R^2 and R^3 are derived based on the relations of the exterior and interior boundary.

Table 1-2 RCC relations in 2D and 3D

RCC Relations	3D	2D
DC(a,b), EC(a,b)		
PO(a,b), EQ(a,b)		
NTPP(a,b), NTPPi(a,b)		
TPP(a,b), TPPi(a,b)		

In the implementation of RCC-3D, the boundary information is marked before determining topological relationships between 3D objects. However, there are several deficiencies in RCC-3D: 1) there is no definition of topological relations between components in R^3; 2) automatic recognition of boundary information must be done before distinguishing relationships (e.g. in the case of a point cloud). Since the boundaries of 3D objects in R^3 have differences in 2D objects in R^2, distinctions between interior and exterior boundaries need to be redefined in R^3. In (Pigot, 1991), the topological relations are determined by the decomposition of a complex 3D object into points, lines, faces, and volumes. The relations of n-simplexes (n-dimensional simplest geometric primitives) are presented in R^2 and R^3, such as the relations between a point and a line segment, a line segment and a line segment, a triangle and a triangle in a 2D space, a triangle and a triangle relations in a 3D space and the relations between volumes in R^3. However, the formal representation of topological relations and the methods deducing these relations are not given.

1.3.5 Feature Recognition

Feature recognition techniques are very useful for obtaining meaningful information from a dataset (Yogeswaran, 2009). Here, feature recognition indicates the process of semantic labeling of geometric features representing object and object components (point, line, and geometric primitives) segmented from point clouds. For example, a plane segmented from point clouds could be a wall, a roof, part of the road, or a component of an object. The process of feature recognition looks for semantics and the meaning of an object to differentiate it from other objects. Some efforts have been made in the development of automatic feature recognition. (Pu, 2009) introduced the knowledge of buildings to reconstruct facades from ground-based laser scanning data. In order to extract meaningful buildings components, such as walls, doors, roofs, protrusions, intrusions, and windows, several characteristics are used for their discrimination, including size, position, orientation, topology, and point density. (Tang, 2010) also mentioned the recognition of doors and windows based on the principle that the laser scanner cannot detect glass.

A semantic network is a graph structure for representing knowledge in patterns of interconnected nodes and arcs. A semantic network may specify the relationships between entities as "floors are orthogonal to walls and doors and parallel to ceilings." Some solutions for automatic modeling based on pre-existing knowledge are developed and tested in the building models (Pu, 2009). Also, other methods related to knowledge-based approaches (Boochs, 2011; Hmida, 2012b; Truong, 2013a) are developed to detect objects from a railway environment and a knowledge-based and heuristic-based method in the modeling of trees (Xu, 2007). The semantic knowledge of urban objects is used to classify objects through the definition of a set of rules for merging segments into meaningful objects. Finally, the objects in the urban scenes are extracted and classified in a hierarchical order ranked by the saliency of the segments (Yang, 2015). Therefore, knowledge-based approaches for feature recognition rely on predefined knowledge about specific types of objects.

For extracting semantically meaningful objects, some machine learning algorithms are explored in feature recognition. Conditional Random Fields (CRF) exploits contextual information in the task of classification. For example, CRF is used as a classifier to classify planar surfaces in a kitchen environment (Rusu, 2009a; Rusu, 2009b), to segment urban scene semantically combining the image and depth point clouds (Wang, 2016a). CRF is also used to classify planar patches in the indoor environment to create 3D models. Other classifiers, such as Support Vector Machine (SVM) and Markov Random Fields (MRF) are also explored and tested in the processing of point clouds (Golovinskiy, 2009; Niemeyer, 2011; Rusu, 2008a; Serna, 2014). Additionally, a Gaussian-Bernoulli deep Boltzmann machine-based hierarchical classifier is used to recognize traffic signs from mobile LiDAR datasets and images (Yu, 2016). The machine learning algorithm stacking and SVM for labeling building elements in an indoor environment (Xiong, 2013) have been proposed. However, the effectiveness of the learning algorithms still needs to be assessed in the case of complex scenes in large-scale urban areas, including buildings, trees, cars, roads, and pedestrians. The results of feature recognition using machine learning algorithms are dependent on the training sets, which is a very complex and costly task.

In summary, the effectiveness of knowledge-based solutions for feature recognition has been demonstrated. For object recognition from point clouds, the hierarchical solution based on the knowledge of specific types of objects is possible to recognize objects according to the contextual information, such as the spatial and topological relations, local geometric properties. The solutions based on machine learning algorithms have a good level of performance for recognizing the features of specific types of objects. However, the training sets for training a classifier determine the precision of recognition results as well. For complex urban scenes, the point density, occlusion, the limited possible characteristics extracted from point clouds, and the quality of training sets all are non-negligible factors that affect the precision of these classifiers for feature recognition. Thus, the solutions based on the combination of point clouds and images are promising to perform well in feature recognition in complex scenes. Similarly, the knowledge-based approaches still need to be improved for dealing with the feature recognition from the point clouds with uncertain information, such as uneven density, occlusion, and incomplete observation.

1.3.6 Creation of a Complete 3D Model

3D geometric models with semantic labels and topological information are widely used in different applications such as indoor navigation and spatial analysis. Incomplete and low-density point cloud with occlusion problems makes 3D modeling for such data very complicated. The complexity of building structures and the variety of building types cause difficulties in creating complete 3D geometric models from incomplete point clouds. In the process of creating geometric models from point clouds, information such as topological relations between object components is critical information that facilitates the 3D modeling process.

Due to incomplete point clouds caused by occlusions, the segmentation results of object components are obviously incomplete. Then, boundary detection and geometric shapes extracted from segmentation results are uncertain. Finally, topologies between building components based on boundaries and geometric shapes cannot represent the topological relations among building components in reality. Therefore, the incomplete 3D geometric models of buildings cannot meet the requirements of spatial analysis in practical applications. In this thesis, we intend to create complete 3D geometric Boundary Representation (B-Rep) building models. The semantic labels of building components recognized from point clouds combining topological relations between building components defined as knowledge can realize this task. The topological relations between building components represented as a topology graph where nodes represent building components and edges indicate the topological relations between them. When the geometric shapes of segments are given semantic labels of building components, the knowledge of building components formalized in the topology graph can help to repair the missing parts of components.

For instance, let's take a closer look at a part of the building such as a roof. There are several types of roofs. Roof types follow certain rules and these rules can be summarized as the knowledge of the roofs, and they can be used to complete roofs (Elberink, 2009). The topology graph is also used to correct the roof topology by identifying the minimum cycle from the topology graph (Xiong, 2015). Since there are only three basic elements to a building topology graph (loose edges, loose nodes, and minimum cycles), all buildings can be deconstructed into predefined basic types. Building primitives are defined according to these basic elements, and the building shape knowledge is included in the process of creating a library of building primitives. After detection of the roof polygons, the correction of the roof topology graph is conducted based on the detected geometric planes and the predefined dictionary for correcting topology (Xiong, 2014). Thus, the roof topology graph is effective in representing the roof topology, and it is further used to correct the topologies detected from point clouds.

However, in the mobile LiDAR dataset, the topology between the building components are more complicated than that among roof components because the topology graph of a whole building could contain a roof, wall, window, door, stair, balcony and protrusion attached to the wall. Due to the unpredictable missing parts caused by occlusion, it is impossible to predict the possible patterns to correct the topology of these components. In contrast, the semantic labels of components are crucial information for predicting the possible missing parts. The topological models among components with semantic labels are predictable and it is possible to be predefined according to the knowledge of building components. Finally, the imperfect connections between the components are promising for correction by the geometric constraints and the knowledge of the components.

1.4 Knowledge Representation and Reasoning

As mentioned, the knowledge base for automatic 3D modeling of urban scenes presents an interesting alternative solution to overcome the limitation of the existing methods especially for feature recognition and the completing of a 3D model. This section presents a review of the foundation of knowledge representation and related concepts. Ontology is an important tool for representing concepts and describing their relations in a formal way. Thus, designing an ontology for describing an urban scene is the first step to integrating knowledge into automatic 3D modeling of urban scenes. Next, the formal representation of knowledge makes it become machine-readable represented with an appropriate language, which is the key step in realizing the reasoning based on predefined rules.

1.4.1 Ontologies

In knowledge engineering, the word "ontology" is a commonly used word. By ontology, we refer to the specification of conceptualization. In Geographic Information Science (GIScience), the study of information and knowledge about geographic reality is an important issue. When terms are used in various ways and domains, the meanings could be different and vague (Guarino, 1995b). Specification of conceptualization allows for a clear definition and distinguishes geographic concepts from each other. Concepts represent all possible things that exist or may exist, including real or abstract things. Geographic concepts can be characterized by different dimensions, including semantics (context, term, properties, relation), reference (spatial, temporal, thematic), semiotics (expression and symbolism) and quality (Kavouras, 2007). Therefore, the creation of ontologies is necessary to clearly define the concepts in the specific domain.

1.4.1.1 Definitions of Ontology

The following definitions of ontology (Table 1-3) are generally used in the literature (Guarino, 1995b):

Table 1-3 Interpretations of ontology at different levels

	Ontology as a philosophical discipline	Definition 1
Knowledge level	Ontology as an informal conceptual system	Definition 2
	Ontology as a formal semantic account	Definition 3
	Ontology as an explicit specification of a conceptualization	Definition 4
Symbolic level	Ontology as a representation of a conceptual system via a logical theory (1) characterized by specific formal properties (2) characterized only by its specific purposes	Definition 5
	Ontology as the vocabulary used by a logical theory	Definition 6
	Ontology as a (meta-level) specification of a logical theory	Definition 7

Ontology (with the capital "O") is used to denote the branch of philosophy that deals with nature and the organization of reality. Ontology tries to answer the question: What is being? Or what are the features that are common to all beings? Ontology studies nature and categories of being and, thus survey general notions such as the essence, existence, properties, modes, necessity, place, time, change, life, etc. For other definitions, ontology is the science of categories (Kavouras, 2007). In definition #2 and #3, ontology is viewed as conceptual "semantic" entities, while in #5 to #7, ontology is a specific "syntactic" object. In definition #3, ontology is expressed in terms of a suitable formal structure at the semantic level. In the 4th definition of ontology, "a formal, explicit specification of a shared conceptualization," formal means that an ontology should be machine-readable. Explicit means that the types of concepts used and the constraints on their use are explicitly defined. Shared means that an ontology captures consensual knowledge that is not private to some individuals but acceptable by a group. Moreover, conceptualization is the key term for clarifying the definition of ontologies.

According to Genesereth and Nilsson's work, a conceptualization is a set of extensional relations describing a particular state of affairs, while the notion we have in mind is an intentional one, namely something like a conceptual grid which we superimpose onto various possible states of affairs (Guarino, 1994). However, in different situations, the same object could be described by different vocabularies, especially in different languages (such as an **apple** in English and une **pomme** in French, both sharing the same conceptualization).

Conceptualization is at the basis of an ontology which is used to formally represent knowledge in an area of interest. Conceptualization is an abstract of the world. A knowledge base, knowledge-based system, or knowledge-level agent is committed to some conceptualization explicitly or implicitly. Essentially, an ontology is an explicit specification of a conceptualization (Gruber, 1995). Conceptualization means that an abstract model of some phenomenon in the world which identifies the relevant concepts of that phenomenon (Studer, 1998).

1.4.1.2 Components of Ontology

In general, ontology consists of four components: concepts, relations, axioms and instances (Stuckenschmidt, 2009). A set of concepts is expressed as a vocabulary of the term used and a specification of the term's meaning. Relations are means for connecting those concepts. Axioms specify constraints or rules about the value of properties, relations, properties of relations and instance, and they are always true. Instances are things represented by concepts. In addition, ontological commitment is a key component of ontology. Ontological commitment is an agreement on the meaning of the vocabulary used to share knowledge (Figure 1-2). Common ontologies are used to describe ontological commitments for a set of agents so that the communication about a domain is not necessary to operate on a globally shared theory. The ontological commitment comes from the knowledge-level perspective. Knowledge is independent of the symbol-level representation. The "action" of agents, including knowledge base servers and knowledge-based systems, can be realized through a "tell and ask" functional interface. Thus, from a pragmatic view, a common ontology defines vocabulary with which queries and assertions are exchanged among agents. Ontological commitments are agreements to use shared vocabulary in a coherent and consistent manner (Gruber, 1995). In short, a commitment to a common ontology is a guarantee of consistency rather than completeness.

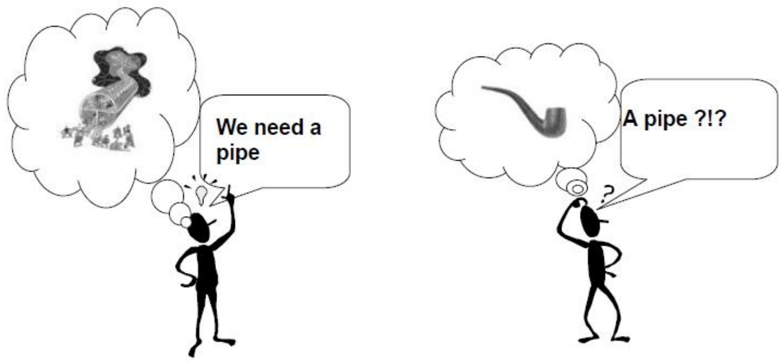


Figure 1-2 The explanation of ontological commitment (Kumar, 2013)

1.4.1.3 Reasons for Applying Ontologies

There are several reasons why we use ontologies. These may include:

- To share common understanding of the information, including people and software agents.
- For the purpose of sharing and reusing domain knowledge. Sharing means that different applications can use the same resources. Reusing means that those components which were built can be used to build new applications. Sharing and reusing knowledge will save money, time and resources. Additionally, it is usually applied in software, knowledge, communications, and interfaces.
- To make domain assumptions explicit. Ontologies will be easier to change domain assumptions and easier to understand and update existed data.
- To separate domain knowledge from operational knowledge.

1.4.1.4 Principle of Designing Ontologies

Based on shared conceptualization, the following criteria are built for designing ontologies for the purpose of knowledge sharing and interoperation (Gruber, 1995).

(1) Clarity. Formalism is a means to make communication effective through defined terms. When a definition can be stated in the logical axiom, it should be clear.
(2) Coherence. An ontology should sanction inference that is consistent with the definition. If a sentence can be inferred from the axiom, but it contradicts a definition or a given example, the ontology is incoherent.

(3) Extendibility. An ontology should be designed to share vocabularies. It should provide a conceptual foundation for a range of tasks.
(4) Minimal encoding bias. The conceptualization should be specified at the knowledge level without depending on the symbol level. Because knowledge agents could be implemented in the different systems and the ways of representation, the encoding basis should be minimized.
(5) Minimal ontological commitment. An ontology should make as few claims as possible about the world model. Since ontological commitment is based on consistent use of vocabulary, only those terms that are essential to knowledge communication are defined.

1.4.2 Semantics

Semantics is defined as the studying of meaning. Meaning is defined as the customary significance attached to the use of a word, phrase or sentence, including both its literal sense and its emotive association. Semantic focuses on the relations between words, phrases, signs, and symbols and the meanings that they stand for.

In the view of the pragmatic level, in computer science, the computer systems need to understand and deal with the meaningful communication and integration of information, which relies on semantic interoperability. Because the notions and terms could mean different things, sharing of information becomes difficult. In such a context, we talk about heterogeneity and vagueness. The communications between systems require an unambiguously understanding of terms. Therefore, semantic interoperability can address the problem of communication. In ontological integration, the identification of heterogeneities is crucial. According to Kavouras (2007), heterogeneities can be classified into three types: syntactic, schematic and semantic (Kavouras, 2007). Finally, the representation normally uses syntax and a schema. Semantics provides meanings by associating the representation in the real world. But syntax and schema cannot provide this meaning.

Additionally, a semantic similarity assessment can be used to assess the relationship between concepts from different ontologies of two or more databases to facilitate data sharing. For example, this may be required where the same geographic area is represented in two different databases where the data from one database may be useful to update the second one (Mostafavi, 2006). For the quality of assessment of spatial databases, the internal consistency can be validated based on ontology. The spatial relationships are checked by way of translating ontology in Prolog and checking for inconsistency in the ontology (Mostafavi, 2004).

In summary, ontologies allow knowledge about objects or phenomena in the world to be represented. Semantics allows for the studying of the meanings of concepts to make the data, concepts, and knowledge interoperable between computer systems. The results of conceptualization can be formally represented using ontology languages in formal ways that allow computers to use them for sharing information in an interoperable way.

1.4.3 Knowledge Representation (KR)

In computer science, Knowledge Representation (KB) is the area of Artificial Intelligence (AI) concerned with how knowledge can be represented symbolically and manipulated in an automated way by reasoning programs. Knowledge representation is a symbolic and formalized process of knowledge to study a general method for the feasibility and effectiveness of knowledge represented by a machine. It is also the unity of a data structure and control structures, considering the storage and usage of knowledge at the same time. Knowledge representation can be seen as a set of conventions to describe things and to represent human knowledge into machine-handleable data structures.

Knowledge representation tries to solve the problem of encoding the knowledge of a human's understanding of reality to make it support reasoning on computers (Kavouras, 2007). For practical purposes, it is commonly agreed that knowledge involves a complex assortment of various cognitive processes. Because the cognitive entails understanding and the ability of reasoning, knowledge essentially is a partial and subjective process during development. When solving a problem, a different approach would represent completely different results. According to Hjørland (2009) so far, people still have not found a common, comprehensive knowledge representation model. There is no sound knowledge representation theory that can be followed. Furthermore, representation is dependent on the knowledge being represented, the subjective views and the interests of people (Hjørland, 2009). There are several important issues to be considered for knowledge representation, including a) which things constitute the knowledge, b) the way of formalizing representation, (c) how inference is supported, and (d) how this representation is implementable (Kavouras, 2007). In addition, as Davis, Shrobe, and Szolovits (Davis, 1993) state: "Representation and reasoning are inextricably intertwined: we cannot talk about one without also, unavoidably, discussing the other." Thus, the knowledge representation involves the factors of subjective, practical problems, the source of knowledge, the formalized way, reasoning, and the implementation.

In accordance with the organization of controlled knowledge classification, the representation can be divided into descriptive representation and procedural representation. Descriptive representation focuses on knowledge, such as objects, events, and facts and their relationships and states. Procedural representation is to emphasize the use of knowledge, focusing on the dynamic aspects of knowledge. However, reasoning is used to prove and answer questions. In the implementation of knowledge representation, the following properties should be considered (Davis, 1993):

1) A KR is an imperfect substitute of a portion of reality and not reality itself.
2) A KR is a set of ontological commitments, or in other words, a KR defines the concepts of the portion of the reality being represented and how this model is built.
3) A KR is a fragmentary theory of intelligent reasoning.
4) A KR is a medium for pragmatically efficient computation. This indicates that a KR must serve practical purposes and be implemented in a machine.
5) A KR is a medium of human expression or, in other words, a medium for human communication.

In summary, a KR should contain the concepts representing the abstraction of reality, the ontological commitments, the implementation of knowledge reasoning on a machine and knowledge sharing. Based on the components of ontology, an ontology and instances constitute a knowledge base.

1.4.4 Formalized Representation of Knowledge

At the symbolic level, ontology needs to be represented by machine-readable language. Recent ontology languages developed within the scope of a semantic web mainly focus on the capability of reasoning, such as OIL (Fensel, 2001), DAML+OIL(W3C, 2001), OWL(Peter F. Patel-Schneider, 2004; W3C, 2012b). In this section, we briefly describe the ontology language that uses a markup scheme to encode knowledge.

1.4.4.1 Description Logics (DL)

DL is a family of formal knowledge representation languages. The DL is used to describe the concepts (classes), role (properties, relations), and individuals (instances of a concept) in a target domain. DLs are represented by formal semantics that is a precise specification of the meaning of DL ontology, which makes humans and computer systems exchange DL ontologies without ambiguity (Krotzsch, 2014). DLs are decidable using first-order logic, and they make sure that the information is possible to be inferred from the facts stated explicitly in an ontology using logical deduction. Another important feature of DL is reasoning, which is the ability to infer knowledge based on a human’s understanding and the tools of computing and giving conclusions.

In DL ontology, concepts represent sets of individuals. Roles represent binary relations between individuals. Individuals represent single objects by names in a given domain. A DL consists of a set of statements (axioms), which is the statement of partial knowledge about the described situation. There are three groups: assertional axioms (ABox), terminological axioms (TBox), and relational axioms (RBox) (Krötzsch, 2012). ABox axioms contain knowledge about named individuals, and they assert facts about concepts. In addition, role assertions describe the relations between individuals. TBox axioms describe relationships between concepts. Constructors (universal quantification (∀), existential restriction(∃), conjunction($\cup$), disjunction($\cap$), equivalence (≡), inclusion($\subseteq$), negation (¬)) are used to represent complex concepts. RBox axioms describe the properties of roles. Based on inclusion and equivalence, some complex concepts are possible to be formed. Transitivity is a special form of complex role inclusion. Based on the axioms, the knowledge can be represented formally through constructors.

OIL, Ontology Inference Layer, aimed at having a well-defined formal semantic with reasoning properties. It is an extension of the Resource Description Framework (RDF) Schema and it is inherited from the DL. OIL is organized as a series of ever-increasing layers of sublanguages. The core OIL coincides with RDFS. Standard OIL captures the necessary modeling primitives. Instance OIL includes individuals (instances), and Heavy OIL has reasoning capabilities. This language is designed based on the ground of Web languages (such as XML, RDFs) and it provides different levels of complexity in terms of formal semantics and reasoning (Horrocks, 2000).

The DAML+OIL ontology language is the extension of the OIL language and the DARPA Agent Modelling Language (DAML) (Horrocks, 2002). It was also proposed as the basis of W3C Web Ontology Language. DAML+OIL is founded on DL and is an expressive DL. DAML+OIL and the defined axioms allow for asserting a subsumption or equivalence to arbitrary expression, including classes and properties.

1.4.4.2 Web Ontology Language (OWL)

Ontology language OWL can be used to explicitly represent meanings of terms in vocabularies and the relationships between terms (W3C). OWL has three sublanguages: OWL Lite, OWL DL, and OWL Full. OWL-Lite allows users to define subsumption hierarchies and simple constraints. OWL-Lite is less expressive because it supports only limited constructs available to define classes, for example, the value of cardinality constraints only permits 0 or 1. OWL DL based on RDF and DL is used to establish an ontology with a very good description of logical reasoning ability. We can use the description logic inference engine for reasoning ontology established on OWL DL for finding hidden information and for achieving more complete reasoning. It supports the users who take the maximum expressiveness and computational completeness and decidability both into account. Thus, OWL Lite has a lower formal complexity than OWL DL. OWL Full is designed for users who want maximum expressiveness and the syntactic freedom of RDF with no computation guarantees. OWL provides classes and their logic constructors (such as intersection, union, disjunction, and other restrictions), properties (transitive and symmetric, datatype properties and object properties), individuals and data value. OWL is the latest recommended language of W3C for publishing and sharing ontologies on the web. OWL 2 extends from the overall structure of OWL 1.

However, OWL 2 adds new functionalities in the aspects of class relationships, properties and data types (W3C, 2012b).

1.4.4.3 Semantic Web Rule Language (SWRL)

Ontology formalized by OWL can describe the logic but it cannot represent Hole-like rules. Thus, a Semantic Web Rule Language (SWRL) is proposed based on a combination of the OWL DL and OWL Lite sublanguages of the OWL Web Ontology Language with the Unary/Binary Datalog RuleML sublanguages of the Rule Markup Language (W3C, 2004). SWRL is capable of representing a high-level abstract syntax for Horn-like rules in both the OWL DL and OWL Lite. SWRL can combine rules and OWL knowledge base together. SWRL extends rules into OWL and it can provide a stronger ability of logical representation. An OWL ontology in the abstract syntax contains facts and axioms, SWRL extends this with rule axioms based on OWL ontology. A rule axiom comprises an antecedent (body) and a consequent (head), such as

$$Axiom \ ::= \ rule$$

Informally, if the antecedent holds, then the consequent must also hold. Each antecedent and consequent is composed of a set of atoms which could be OWL class, properties, built-in relations, individuals or data value. When a relatively informal "Human Readable Syntax" form is used to represent a rule, it is described as follows.

$$antecedent \Rightarrow consequent$$

When both antecedent and consequent are conjunctions of atoms, a rule can be written as:

$$a_1 \wedge a_2 \wedge ... \wedge a_n \Rightarrow consequent$$

For example, the fact that a supervisor is a professor who supervises student can be written as:

$$Professor(?x) \wedge Supervise(?x, ?y) \wedge Student(?y) \Rightarrow Supervisor(?x)$$

SWRL can describe some rules that DL cannot, which makes it is possible to describe the complex knowledge. SWRL realizes the capabilities of the expressiveness of knowledge in a domain and the inferring new knowledge in the formal knowledge representation and reasoning. Some reasoners, such as FaCT++, Pellet, HermiT and RACER and Jena, are able to infer logical consequences from a set of facts and axioms. Thus, the integration of OWL, SWRL, and semantic reasoners provides the framework for the reasoning on provided knowledge in the practical applications related to knowledge-based solutions.

1.5 Methods of Uncertain Reasoning in Automatic 3D Modeling

In the following, we introduce uncertain projective geometry for reasoning geometric relations and Dempster-Shafer (D-S) evidence theory. Uncertain projective geometry (Heuel, 2004) is built on homogeneous coordinates. The framework of uncertain projective geometry allows reasoning about spatial relations between geometric shapes (points, lines, and planes) detected from images. However, it can also be used in the identification of geometric relations between geometric shapes extracted from point clouds. In this thesis, uncertain projective geometry framework is chosen to translate geometric relations between object components extracted from segmentation results into semantic descriptions (such as parallel, perpendicular) that are used as relations between the individual concepts in the ontology.

In addition, as mentioned previously, the feature recognition step has the challenges of semantic labeling of objects and components from segmentation results with uncertainty. We chose the Dempster-Shafer (D-S) evidence theory to solve the problem. First, the properties and relations of segments are formalized as semantic descriptions. Then after comparing the similarities between these properties and relations of segments and those defined in the semantic rules in the knowledge base, the most appropriate rule that helps to recognize this segment is selected. Finally, the properties and relations of segments contained in the appropriate rule are considered evidence to reason about the semantic label of this segment. In D-S theory, the uncertainties of the properties and relations related to this segment are combined together to obtain the support level of a certain semantic label to this segment.

1.5.1 Uncertain Projective Geometry for Reasoning about Geometric Relations

Homogeneous coordinates, a system of coordinates applied in projective geometry, as Cartesian coordinates used in Euclidean, can be adopted in geometric reasoning for spatial relationships of shapes belonging to a single object. Homogeneous coordinates have the advantage that the coordinates of points, including points at infinity, can be represented using finite coordinates. A point (x, y) on a Euclidean plane is represented with (X/t, Y/t), while the triple (X, Y, t) = (xt, yt, t) where $t \neq 0$, is a set of homogeneous coordinates for the point (x, y). A line can be expressed using a parametric equation as x= a+mt, y=b-nt. Let Z= 1/t, a point on a line can be defined as ((aZ+m)/Z, (bZ-n)/Z). With homogeneous coordinates, it becomes (aZ+m, bZ-n, Z). When t approaches infinity, (m, -n, 0) are defined as homogeneous coordinates of the point at infinity corresponding to the line direction. Finally, the various expressions of a line are represented as the only form. Hence a more general framework provided by projective geometry (Heuel, 2004) is helpful for geometric reasoning because Euclidean geometry is not sufficient to represent infinite elements.

Table 1-4 Representations of geometric relations (Heuel, 2004)

Geometric relation	Algebraic representation	Projective representation
Plane A $\perp$ Plane B	$C = A_h{}^T B_h = 0$	Plane A= $\left(a,\ b,\ c,\ d\right)$
Line L || Plane A	$C = L_h \times A_h = 0$	Line L= $\left(L_h,\ L_0\right) = (A_h \times B_h, A_0 B_h - B_0 A_h)$
Plane A || Plane B	$C = A_h \times B_h = 0$	
Line L || Plane A	$C = L_h{}^T A_h = 0$	
Point X $\in$ Plane A	$C = X^T A_h = 0$	Point X= $\left(tx,\ ty,\ tz, t\right)$
Point X $\in$ Line L	$C = X^T A_h = 0$ and $X^T B_h = 0$	

In order to realize geometric reasoning by machine, the conversion of the geometric relationship to an algebraic formulation is a key step. Since geometric shapes can be expressed via multivariate polynomials, the coordinate-based finite geometries need to be transferred to a projective geometry representation using homogeneous coordinates. In this method, planar surfaces can be represented by the plane equation: $a_i x + b_i y + c_i + d_i = 0$. It will become $\Pi_i = ((a_i, b_i, c_i), d_i) = (n_i, d_i)$ after the projective processing, where n_i is the normal vector of the plane. A line is represented by the intersection of two planes, that is $L = \left(L_h,\ L_0\right) = (A_h \times B_h, A_0 B_h - B_0 A_h)$. Therefore, geometric relationships, such as parallelity, orthogonality, collinearity, and coplanarity, can be represented by the corresponding homogeneous coordinates as shown in Table 1-4. Finally, the fundamental geometric relations can be determined by vector computation.

The geometric reasoning from projective geometry is supported by a statistical test approach based on the homogeneous representation of geometric entities (Koch, 1999). First, the determination of the geometric relations between geometric entities relies on a hypothesis test. The statistical test proposed by Heuel (Heuel, 2004) is designed to realize geometric reasoning from geometric entities with uncertainty. Because the uncertainty of a vector x is assumed to be normal distribution, a geometric entity is represented as a pair (x, Σ_{xx}) with its covariance matrix Σ based on this assumption. The first order error propagation is applied in the geometric relations reasoning and the error is propagated through all the operations, such as transformation and construction (Loch-Dehbi, 2011). For homogeneous entities $F(x) = y\ =\ Ax + b$ transformed from a Euclidean vector x with a linear transformation, the first-order error propagation of this transformation is $\Sigma_{yy} = A \Sigma_{xx} A^T$ (A is the Jacobian of $F(x)$). Similarly, the uncertainty of y for a homogeneous vector (y, Σ_{yy}) is also given. Finally, the geometric relation $R(x, y)$ is represented as a matrix-vector multiplication. The hypothesis of R is represented as follows (Heuel, 2004):

$$R(x,y) = U(x)y = V(y)x \qquad \textbf{(Eq 1-4)}$$

Here, x and y are geometric entities. $U(x) = \partial R / \partial y$ and $V(y) = \partial R / \partial x$ are the Jacobian of R with respect to x and y. R is the geometric relation.

The following formula is used to calculate the covariance matrix of R:

$$\sum_{RR} = (V(y), U(x)) \begin{pmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{xy} & \Sigma_{yy} \end{pmatrix} \begin{pmatrix} V^T(y) \\ U^T(x) \end{pmatrix} \qquad \textbf{(Eq 1-5)}$$

Finally, the geometric relations between geometric entities become a hypothesis test problem. It is a chi-square test. Herewith, the geometric relations orthogonality, parallelity, and incidence can be determined by this hypothesis test. The critical value $\chi^2_{r,1-\alpha}$ is defined by a given significant level ($1-\alpha$) and the degree of freedom r.

$$R^T \sum\nolimits_{RR}^{-1} R > \varepsilon_H = \chi^2_{r,\,1-\alpha} \qquad \textbf{(Eq 1-6)}$$

If the above condition holds, this hypothesis will be rejected. The probability α is chosen as a small number such as 1% to 5%.

In summary, based on uncertain projective geometry, the determination of geometric relations between geometric entities is transformed into the problem of the hypothesis test. The uncertainties of geometric entities are propagated in the processes of creating geometric relations and deciding if this hypothesis of geometric relation can be rejected. In this thesis, the geometric relation between object components detected from point clouds with uncertainties is decided based on the hypothesis test, which is robust to deal with the identification of geometric relations from segmentation results with uncertainties.

1.5.2 Dempster-Shafer (D-S) Evidence Theory

Dempster-Shafer (D-S) theory is a mathematical theory of evidence. In essence, D-S theory can be viewed as a generalization of traditional probability theory. In the probability theory, the probabilities are assigned to mutually exclusive events. In D-S theory, the probabilities are defined for the sets where evidence could be associated with multiple events. However, in traditional probability theory, the evidence is associated with one possible event. Therefore, the possible events in probability theory cannot occur at the same time. However, the sets of events could have some intersections in D-S theory. As a result, evidence has a higher level of abstraction without resorting to further assumptions of the probability distribution in a set (Sentz, 2002). In conclusion, D-S theory is a framework for representing and handling uncertain evidence by combining the evidence expressed as a notion of probability with the traditional concept of sets.

1.5.3 Definitions

When $X = (x_1, x_2, ..., x_n)$ is the universal set (Forster, 1992) which contains all elements, including X, is called as discernment frame where containing n distinct elements x_i ($i = 1, 2, ..., n$). The power set of X, represented by Θ, is the set containing all possible subset of X. There are 2^n elements in Θ.

Basic Probability Assignment (BPA) is the basic of D-S theory. However, it is not the same as the probability in the classic sense in the probability theory. BPA is a function that maps power set Θ to [0, 1]. It is also called mass function.

$m : \Theta \to [0,1]$. $A \mapsto m(A)$, which satisfies:

$$\begin{cases} m(\varnothing) = 0 \\ \sum_{A \subseteq \Theta} m(A) = 1 \end{cases} \quad \textbf{(Eq 1-7)}$$

Where $\varnothing$ is the null set, and A is a subset of the power set Θ. When $m(A) > 0$, A is called as a focal element.

The description of an event uses the interval [$Bel(A)$, $Pl(A)$] consisting of belief function and plausibility function. Bel(A) indicates the support level of event A, Pl(A) means the level that can’t deny the even A. The belief function and plausibility function are defined as:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad \textbf{(Eq 1-8)}$$

$$Pl(A) = \sum_{B \cap A \neq \varnothing} m(B) \quad \textbf{(Eq 1-9)}$$

The belief function represents the sum of all the BPA of the subsets of the given set. The plausibility function is the sum of all the BPA of sets intersecting with the given set. For example, if an interval (0.25, 0.65) represents the uncertainty of event A, it means that the belief of “event A is true” is 0.25 and the belief of “event A is false” is 0.35. Thus, the uncertainty of event A is 0.4.

1.5.4 Combination Rules of Evidence

For arbitrary $A \subseteq \Theta$, the combination of evidence is based on the normalized conjunction operation (Shafer, 1976). The mass functions should be defined in the same frame of discernment, and they are viewed as independent arguments. The Dempster combination rule is defined as:

$$m_{12\cdots n}(A) = (m_1 \oplus m_2 \oplus \cdots \oplus m_n)(A) = \begin{cases} 0, & A = \varnothing \\ \dfrac{1}{1-K} \sum\limits_{A_1 \cap A_2 \cap \cdots \cap A_n = A} m_1(A_1) \bullet m_2(A_2) \cdots m_n(A_n), & A \neq \varnothing \end{cases} \qquad \textbf{(Eq 1-10)}$$

where $K = \sum\limits_{A_1 \cap A_2 \cap \cdots \cap A_n = \varnothing} m_1(A_1) \bullet m_2(A_2) \cdots m_n(A_n)$

Here, 1-K is the normalized factor. K represents the degree of conflicts among the mass functions. It is calculated by the sum of the products of the mass function of all sets where there is no intersection. This combination rule conforms to commutative and associative. Thus, when using the combination rule in practice, the combination operation can be realized by combining two pieces of evidence firstly and then this result is used to combine other evidence. However, this rule will yield a counterintuitive result when some conflicting evidence is chosen for the combination. A typical example is that a patient is seen by two doctors. According to his symptoms, the first doctor gives the conclusion that the probability of disease A is 0.99 and 0.01 for B. However, the second one believes that the probability of 0.01 for C and 0.99 for B. This case is counterintuitive. That is, in the frame of discernment $X = (A, B, C)$, two evidence are: $m_1(A) = 0.99$, $m_1(B) = 0.01$, $m_1(C) = 0$, and $m_2(A) = 0$, $m_2(B) = 0.99$, $m_2(C) = 0.01$. If two pieces of evidence are used to calculate the combined m_{12} with Dempster's rule, the conclusion will be $m_{12}(B)$=1. In fact, two doctors give different conclusions (Zadeh, 1984). Apparently, this combination rule produces an unreliable result that indicates complete support for certain diagnoses.

Some methods and some new combination operations have been developed aiming at solving the conflict in the process of combining the evidence. The main idea of decreasing conflicts firstly is to discount the evidence and then to combine them with Dempster's rules or an alternative rule. Such as Shafer (Shafer, 1976) applied the degree of reliability 1-α_i ($0 \le \alpha_i \le 1$) to a particular belief function. The discounted belief function is defined as $Bel^{\alpha i}(A) = (1-\alpha_i)Bel(A)$. Finally, the averaged belief function associated with set A will get an average of n belief function. However, this method decreases all belief functions even if some of them are reasonable. Yager (Yager, 1987) modified the Dempster combination rules through the notion of a quasi-associative operator (Ronald R, 1987). In Yager's rules, the evidence is not changed by normalizing out the conflict. The mass function related to the conflict is allocated to the universal set instead of the null set. Other solutions for combining conflict evidence are Zhang's rules (Zhang, 1994), Inagaki rules (Inagaki, 1991), the mixing or averaging method (Zhang, 1994), weighted evidence (JIA, 2012; Pal, 1993; Xing, 2016a) and so on. In conclusion, the D-S theory can be used to fuse multi-source data and obtain the probabilistic fusion conclusion. It is a good solution for making a decision from uncertain multi-source data. However, when there is some conflicting evidence, the conclusion after combining evidence is dependent on the methods of handling the high conflict case.

1.6 Machine Learning Algorithm for Classification

1.6.1 Support Vector Machine (SVM) Learning Algorithm

SVMs are supervised learning methods that are very effective for the classification of high dimensional data. SVMs have a rigorous theoretical foundation and have good performance in practice (Roobaert, 1999). SVMs are linear classifiers that find a hyperplane to separate two classes of data. In addition to having very good performance for linear classification problems, SVMs can efficiently perform non-linear classification using kernel functions (Linear, Polynomial, Sigmoid, Gaussian RBF) that implicitly map inputs into high-dimensional feature spaces. SVMs can employ different training algorithms to minimize an error function: C-SVM and nu-SVM for classification, and epsilon-SVR and nu-SVR for regression (Chang, 2011). Moreover, cross-validation is used to estimate the generalization performance of a model. The k-fold cross-validate indicates that the training set is split into k smaller sets to learn a model for avoiding the overfitting case. k is defined by the requirements of the practical application. In summary, although SVMs require training sets to train a classifier, it showed that SVMs are not sensitive to training sample size after literature review. SVMs still can successfully work on a limited quantity of training sets (Mountrakis, 2011).

In previous studies, SVMs with different kernel functions were used to learn 3D geometric primitives using point feature histograms based on viewpoint. The results show that SVMs have very good performances in complex noisy scenes (Rusu, 2008a) (Figure 1-3). SVMs were also used to classify natural objects and to evaluate local geometry at different scales (Brodu, 2012). More applications related to the classification using SVMs in remote sensing are presented in the review article (Mountrakis, 2011).

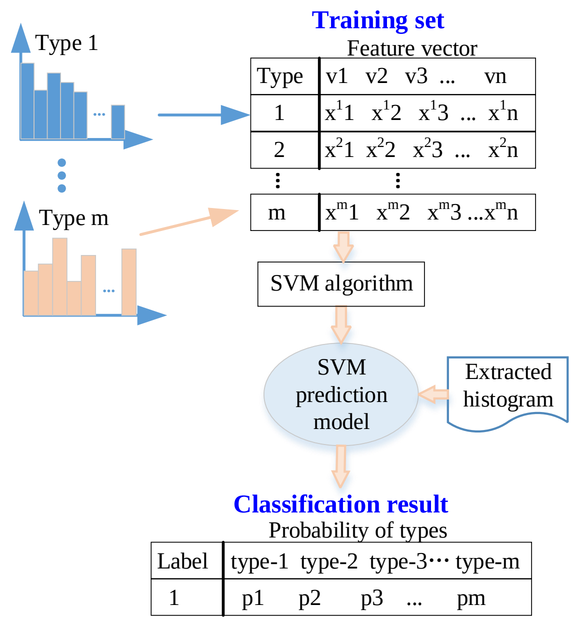


Figure 1-3 Detailed descriptions of learning geometric primitives from the histogram

1.6.2 Random Forest Classifier

Random forest (Breiman, 2001)is composed of a collection of decision trees constructed using random features sampled independently. Each tree is trained on the training set based on bootstraps that create a random resampling on the training set itself, and random features are selected to create trees (Svetnik, 2003). The prediction is decided by aggregating the predictions of decision trees. Each node in a binary decision tree represents a feature selected for splitting samples into two classes. Gini impurity measures how well a potential split is in this node (Menze, 2009). The formula of Gini impurity is:

$$Gini(m) = 1 - \sum_{i=1}^{C} (p_i)^C \qquad \textbf{(Eq 1-11)}$$

Where $p_i = n_k/n$ is the fraction of n_k samples from C classes out of the total of n samples at node m.

The advantages of the random forest are that it is straightforward to deal with multi-class problems, that it is easy to parallelize its implementation and that it demonstrates good results on large-scale point clouds in a reasonable time. The usage of random forest for classification of problems is the same as the steps stated in Figure 1-3, including the definition of features, the preparation of feature vectors for training a model, training a classification model based on training sets and evaluating the results of testing sets using the trained classification model. The evaluation of a random forest classifier can provide the importance of features in addition to the precision of the classification results. It is better to know which features play a critical role in the classification model and it is helpful to adjust features for learning a model in practical applications.

1.7 Discussion

Automatic 3D modeling of an urban scene from point clouds is a complex task. The LiDAR technologies make it possible to quickly scan an urban scene. In this chapter, the usage scenarios of different types of scanning devices and the quality of observation are summarized. We then summarize the algorithms for classification, object detection and segmentation of point clouds. The segmentation algorithms are compared and classified into edge-based, scanline-based, region-growing, model fitting and clustering-based methods. We also analyze the limitation of these algorithms. After the summarization of segmentation algorithms, topologies in 2D and 3D are introduced and the necessity of developing the topologies among object components in 3D geometric B-Rep models is discussed. Based on the above work, an improved pointwise semantic segmentation algorithm, a solution for CAD-like segmentation of complex buildings and the definition of the topological relations between object components will be developed in the thesis.

The knowledge of an urban scene plays a vital role in feature recognition. For automatic feature recognition, formalized knowledge of urban scenes bridges between the abstraction of urban scenes and the segmentation results of point clouds. The literature review demonstrates that feature recognition depends on the predefined rules where information extracted from segmentation is used to reason about the object. The rules can be defined by the constraints of size, position, orientation, topology, and geometric relations with other objects. In addition, we argued that when the geometric and topological information extracted from segmentation results are uncertain, the feature recognition process, as well as 3D modeling, becomes more complicated. Thus, the knowledge representation and the methods of uncertain reasoning that can be used to deal with uncertainties in feature recognition are discussed. Meanwhile, we introduce their usage in the corresponding chapters and their roles.

For the goal of creating complete semantically enriched 3D geometric models, it is feasible to make use of extracted semantic information of objects for the completion of geometric models. According to the knowledge of object components, the possible connections between components, especially for man-made objects, are viewed as the constraints to correcting the geometric models. For instance, some studies showed that the predefined topologies among roof components are effective in correcting the roof topologies extracted from point clouds. Similarly, based on the semantic information of object components, the inherent constraints among components is promising information for correcting imperfect geometric models.

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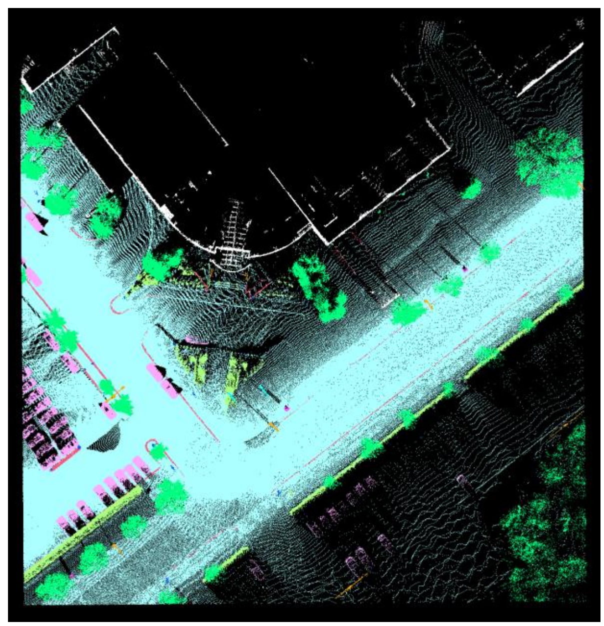
Introduction of Article

An Improved Automatic Pointwise Semantic Segmentation of 3D Urban Scene from Mobile Terrestrial and Airborne LiDAR Point Clouds: A Machine Learning Approach

Automatic semantic segmentation of point clouds observed in a 3D complex urban scene is a challenging issue. Pointwise semantic segmentation of point clouds gives a semantic label to each point. Semantic segmentation directly predicts object class at point level, which is helpful to identify object components and topological relations between components. Chapter 3 is a paper where we propose to solve the problem of automatic semantic segmentation of urban scene from point clouds. For example, in the following figure, the input point cloud and the expected results of semantic segmentation are shown. In the expected result, points with same color indicate the points belong to same object class.

(A) Input point cloud



(B) The result of semantic segmentation

Figure IV the expected work of automatic semantic segmentation

For the purposed of semantic segmentation of urban scene from airborne and terrestrial LiDAR data, in this paper, we propose features derived from Difference of Normal and directional height difference between neighbors as inputs of random forest classifier in addition to features derived from eigenvalues, moments around eigenvectors and elevation. Here the term “feature” is introduced from the field of machine learning.

A feature is defined as an individual measurable property or characteristic of a phenomenon being observed. Random forest classifier is chosen to classify point clouds based on the proposed features and existed features derived from eigenvalues, moments around eigenvectors and elevation due to its robustness and less-sensitiveness of parameters. The experiments show that the proposed features are effective to improve the accuracy of semantic segmentation of mobile and airborne LiDAR point clouds in urban scenes, especially for vegetation and building classes.

CHAPTER 2 An Improved Automatic Pointwise Semantic Segmentation of 3D Urban Scene from Mobile Terrestrial and Airborne LiDAR Point Clouds: A Machine Learning Approach

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2.1 Résumé

La segmentation sémantique automatique des nuages de points observés dans une scène urbaine complexe en 3D est un problème très difficile. La segmentation sémantique de scènes urbaines basée sur un algorithme d'apprentissage automatique requiert des fonctionnalités appropriées pour distinguer les objets des nuages de points LiDAR terrestres et aéroportés mobiles au niveau des points. Dans cet article, nous proposons une méthode de segmentation sémantique par points basée sur les caractéristiques proposées dérivées de Différence de normale et les caractéristiques «hauteur directionnelle supérieure», qui compare la différence de hauteur entre un point donné et les voisins dans huit directions, en plus des caractéristiques basées sur la normale estimation. Un classificateur de forêt aléatoire est choisi pour classer les points dans les nuages de points LiDAR mobiles terrestres et aéroportés. Les résultats obtenus à partir de nos expériences montrent que les caractéristiques proposées sont efficaces pour la segmentation sémantique des nuages de points LiDAR mobiles terrestres et aéroportés, en particulier pour la végétation, les bâtiments et les classes de sol dans des nuages de points LiDAR aéroportés en zone urbaine.

2.2 Abstract

Automatic semantic segmentation of point clouds observed in a 3D complex urban scene is a challenging issue. Semantic segmentation of urban scenes based on machine learning algorithm requires appropriate features to distinguish objects from mobile terrestrial and airborne LiDAR point clouds in point level. In this paper, we propose a pointwise semantic segmentation method based on our proposed features derived from Difference of Normal and the features “directional height above” that compare height difference between a given point and neighbors in eight directions in addition to the features based on normal estimation. Random forest classifier is chosen to classify points in mobile terrestrial and airborne LiDAR

point clouds. The results obtained from our experiments show that the proposed features are effective for semantic segmentation of mobile terrestrial and airborne LiDAR point clouds, especially for vegetation, building and ground classes in an airborne LiDAR point clouds in urban areas.

Keywords: semantic segmentation, 3D urban scene, 3D LiDAR point cloud

2.3 Introduction

With the rapid development of LiDAR technologies, airborne and terrestrial LiDAR datasets are widely used as an important source of geospatial information for various applications ranging from 3D mapping to urban planning, land surveying, building reconstruction, 3D city modeling and digital heritage management (Yang, 2013). Generally, LiDAR data processing and modeling steps take tremendous time and operator efforts compared to the data acquisition step (Knaak, 2012). To address this issue, the automation of LiDAR data processing is very important to help to better benefit from the richness of data. Semantic segmentation is one of those important steps in LiDAR data processing that needs to be automated especially for real-time applications.

Semantic segmentation of point clouds directly gives semantic labels to points for better understanding scenes recorded in a point cloud. The efficiency of this process is important in applications such as self-driving cars that navigate themselves by integrating LiDAR scanners to observe the surrounding areas (Fisher, 2013), or on-the-fly decision-making for secure navigation and localization. Furthermore, dynamic environment maps and real-time semantic 3D object maps are important prerequisites in motion planning for robot self-navigation as well (Rusu, 2010). In addition, semantic segmentation is required in applications such as cliff recognition to evaluate sea cliff changes (Young, 2010) or detecting transport network obstructions by comparing airborne LiDAR data before and after disasters to shorten the time of reaching disaster sites (Kwan, 2010). In some practical applications, identifying points representing terrain topography from airborne LiDAR point clouds is a fundamental requirement. However, extraction of the topography in urban areas is more complex as tunnels and bridges are not easy to be detected from airborne LiDAR point clouds. Semantic segmentation is promising to classify airborne LiDAR point clouds to deal with varying topography based on appropriate features.

In this paper, we present an improved pointwise semantic segmentation of an urban scene from mobile terrestrial and airborne LiDAR point clouds. Inspired by multi-scale features for classifying points defined in (Hackel, 2016), we propose features derived from Difference of Normal (DoN) for better identifying geometric properties of the surface of different objects. The feature "directional height above" that compares height difference between a given point and its neighbors is defined to improve the semantic segmentation of airborne LiDAR point clouds especially for building and ground classes. This allows training models in an urban area with buildings and relatively flat ground. The method is robust enough to segment scenes with changing topography and buildings with different dimensions. Random forest classifier is chosen to classify points based on existed features and new proposed features. The results obtained from several experiments show that the proposed method with newly defined features is effective to improve the semantic segmentation of airborne and mobile terrestrial LiDAR point clouds, especially to differentiate ground, buildings, and vegetation from airborne LiDAR point clouds in urban areas.

The remainder of this paper is structured as follows: we present related works in Section 2. Sections 3 presents the proposed method and define the features for semantic segmentation in details. Section 4 presents experiments on mobile and airborne LiDAR point cloud and the analysis of experimental results. Finally, Section 5 concludes this work and presents some perspectives on future work.

2.4 Related Work

Automatic semantic segmentation for deriving information on individual objects from LiDAR point clouds is a difficult task (Hackel, 2016). Segmentation is the process of partitioning a point cloud into groups with homogeneous properties where all points belonging to a group have the same meaningful label (for example, points belonging to a geometric primitive such as a plane) (Awwad, 2010; Rabbani, 2006). Similarly, semantic segmentation of point clouds gives a semantic label to points representing the same object class (for example a wall or a building). Knowledge-based and machine learning methods are among the approaches that are proposed for the extraction of semantic information from point clouds in urban areas. Knowledge-based methods for extracting semantic information from point clouds have been explored in segmentation, feature extraction, and object recognition from point clouds. (Pu, 2009) extracted semantic features using semantic rules for the reconstruction of building facades from point clouds. (Boochs, 2011), (Hmida, 2012b) and (Truong, 2013a) used semantic knowledge in all point cloud processing stages for object detection based on three modules including a built knowledge module, an algorithm selection module, and a semantic qualification engine. (Xing, 2018) proposed a knowledge base for feature recognition from point clouds of urban scenes. The prior knowledge about objects is formalized as semantic rules based on ontology in which contains several modules for describing urban scenes from different perspectives. Among them, the spatial relations module allows formalizing possible topological relations among object components extracted from point clouds. The geometric properties and topological relations between object components extracted from point clouds are viewed as facts to infer semantic information of objects, such as recognizing complex geometry, building roof styles and building components.

Machine-learning algorithms are used to extract semantic information from point clouds. For the indoor environment, Rusu (Rusu, 2009b) used Conditional Random Field (CRF) to label small indoor point clouds based on Fast Point Feature Histograms (FPFH) derived from planar segments. Xiong (Xiong, 2013) employed region growing algorithms to detect planar patches from a voxelized point cloud of inner structures of buildings and then used the "Stacking" learning algorithm to classify patches. Then, the patches are annotated with semantic labels of building components. In their work, the features are designed for a group of points in planar segments and the classification is conducted based on the features of planar segments. Armeni (Armeni, 2016) proposed a hierarchical approach for semantic parsing point cloud of an entire building in an indoor space into semantically meaningful spaces at the first level, and spaces parsed into building elements wall, columns in the second level. For identifying building elements, 3D sliding windows are used to slide candidate windows from large-scale point clouds. Then, for each voxel, features including position, size, surface normal, curvature, occupancy, and ratio, were derived from points in the voxel. Structured SVM classifier is chosen to classify candidate windows. This method is effective to segment indoor environment of buildings. Semantic segmentation based on the features of candidate windows can fast segment large indoor scenes. However, the features of candidate windows will not perform well for the semantic segmentation of complex urban scenes. For the outdoor environment, pointwise semantic segmentation of point clouds directly gives semantic labels to points, which is a straightforward way to understand scenes. Weinmann (Weinmann, 2013) studied feature relevance assessment based on geometric 2D and 3D features and analyzed the impact on the semantic interpretation of 3D terrestrial LiDAR point cloud data using four classifiers. The experiments are conducted on a terrestrial LiDAR point cloud representing an urban environment containing smooth ground. For improving the distinctiveness of 2D and 3D geometric features, the optimal size of neighborhood selection for individual points is explored based on the definition of Shannon entropy (Weinmann, 2015). The multi-scale features extended from (Weinmann, 2013) for dealing with varying point density are used in semantic segmentation of urban areas observed by terrestrial LiDAR. This is a supervised pointwise classification of mobile LiDAR point clouds of urban areas using a random forest classifier that is simple but powerful and has good generalization ability (Hackel, 2016). Moreover, Niemeyer (Niemeyer, 2012) used a CRF to classify urban scenes with flat ground in a point cloud. The fundamental element of machine-learning methods is the definition of features. The features are designed according to nature of segmentation (pointwise or voxel). Meanwhile, the design of features for semantic segmentation of mobile terrestrial LiDAR as well as airborne LiDAR point clouds should consider the variety of objects. For example, height difference in a local area is effective to distinguish ground and buildings, but not effective for tunnels and for varying change of ground. This is because the ground close to the edges of a tunnel will be classified into building class. Therefore, it is necessary to define new features that allow better distinction between tunnels, buildings in the topography itself.

In addition, other solutions based on deep learning for semantic segmentation include Pointnet (Qi, 2017), PointCNN (Li, 2018) and deep learning on multiple 2D image views (or snapshots) of the point cloud (Boulch, 2018). However, these methods need a massive volume of training sets. For practical applications, it is not easy to collect a good training set, especially for semantic segmentation of large-scale mobile terrestrial and airborne LiDAR point clouds.

In summary, knowledge-based methods for extracting semantic information on objects require pre-built rules or knowledge base to infer semantic information combining the information extracted from point clouds. This method is difficult to be applied in point level and if it is used in a large-scale urban scene, the knowledge base containing appropriate rules is essential to recognize different types of objects. A large volume of the pre-labeled training set is needful to deep learning algorithms for semantic segmentation of urban scenes. However, it is possible to obtain good results of semantic segmentation without the need for a large volume of training set if the appropriate features are defined for machine learning methods of semantic segmentation of urban scenes.

2.5 Method

Machine learning based semantic segmentation includes three steps: define features for training a classification model, train classification models on a training set based on defined features and evaluate the classifier performance on a testing set. Pointwise semantic segmentation requires to define a feature vector for each point. Then the feature vectors derived from the training set are input into machine learning classifier to train a model. Similarly, feature vectors obtained from the testing set are given to the trained model to classify points for evaluating the classification results.

2.5.1 Definition of Features for Pointwise Semantic Segmentation

2.5.1.1 Normal Estimation

Within a point cloud, surface normal estimation at a given point requires the information on its neighbors in a local area (Klasing, 2009). There are several methods for selecting neighbors, including fixed number neighbors selection and fixed radius neighbor selection. Due to the presence of uneven density and occlusion in point clouds, the fixed number neighbors selection allows ensuring the selection of the required points for the estimation of the surface normal. Although, this may introduce some uncertainty in the estimation process. In this paper, the optimal neighbor size is selected using the general definition of the Shannon Entropy (Weinmann, 2014). When the neighbors are chosen, the Principal Component Analysis (PCA) is used to estimate the normal. According to the approach, the local surface covariance matrix C is expressed as:

$$C = \frac{1}{k}\sum_{i=1}^{k}(p_i - \overline{p}) \bullet (p_i - \overline{p})^T, \quad C \bullet v_j = \lambda_j \bullet v_j \quad j \in \{0,1,2\} \qquad \textbf{(Eq 2-1)}$$

Where C is a 3*3 symmetric and positive semi-definite matrix.

$\overline{p}$ is the centroid

p_i indicates the neighboring point

λ_j is eigenvalue

v_j is eigenvector

After using Singular Value Decomposition (SVD), its eigenvalues λ_j and the corresponding non-zero eigenvectors v_j are solved. These eigenvectors are orthogonal to each other. In a point cloud with 3D coordinates, if eigenvalues $\lambda_2 > \lambda_1 > \lambda_0 > 0$, the two largest eigenvectors can approximately determine a plane and the eigenvector corresponding to the smallest eigenvalue is its orientation, or normal (Rusu, 2009a). Therefore, the eigenvector corresponding to λ_0 is the approximation of the normal ($+\vec{n}$ or $-\vec{n}$). The known viewpoint and the Riemannian graphs (Hoppe, 1992) can be used to make normal directions uniform. Additionally, the curvature (surface variation) at p_i is defined as:

$$\sigma(p_i) = \frac{\lambda_0}{\lambda_0 + \lambda_1 + \lambda_2} \qquad \textbf{(Eq 2-2)}$$

2.5.1.2 Definition of Multi-scale Features for Semantic Segmentation

For a large-scale urban scene, the extraction of multi-scale features from dense point clouds requires huge computation capabilities within a given range of selected neighbors. Decreasing the point density in a large range is necessary to balance computation cost and time. The strategy of downsampling (Brodu, 2012; Hackel, 2016) point clouds makes it possible to select a fixed number of nearest neighbors for different scales (Figure 2-1). The point cloud is downsampled by generating a pyramid of scales using different voxel sizes. For a given point in the original point cloud, the fixed number of neighbors is picked up at each scale level. The voxel filter is a widely used method for downsampling 3D point clouds. The bounding volume of the point cloud is divided into small voxels of a given size, and the points in each voxel are replaced by the centroid of the point set. Based on the normal estimation in a point cloud, several features for the characterization of objects (as shown in Table 2-1) are derived (Gross, 2006; Hackel, 2016; Wang, 2015) at different scales.

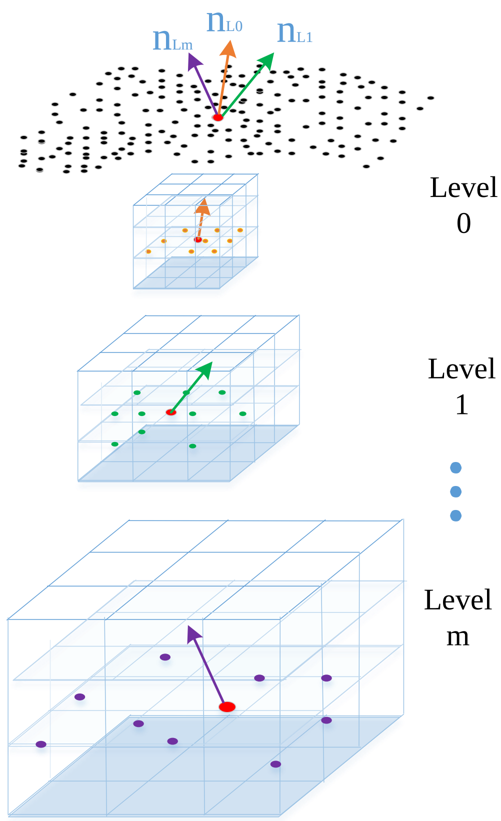


Figure 2-1 Illustration of downsampling a point cloud at different scales

We also propose to calculate height above feature based on sliced point cloud in 8 directions (east, south, west, north, southeast, southwest, northeast and northwest) (as shown in Figure 2-2). For each point P, we slice point cloud in 8 directions on P. The height difference is calculated based on the endpoints of smooth line segments. For example, in Figure 2-2 (B), point P1 is an endpoint of the segment containing current point P because there is a sharp change on point P1 when the line segment grows from P to P1. Similarly, point P2 is an endpoint of another smooth line segment containing the lowest points. The sliced height above feature is computed by the height difference between two neighboring endpoints belonging to different line segments (P1 and P2). The sliced height above features are calculated in eight directions, and they are computed in the level 0 of the downsampled point cloud.

Table 2-1 Features for semantic segmentation of urban scenes from LiDAR point clouds

Features in (Hackel, 2016)	Covariance	Sum	$\lambda_1+\lambda_2+\lambda_3$
		Omnivariance	$\sqrt[3]{\lambda_1 \cdot \lambda_2 \cdot \lambda_3}$
		Eigenentropy	$-\sum_{i=1}^{3}\lambda_i \cdot \ln(\lambda_i)$
		Anisotropy	$(\lambda_1-\lambda_3)/\lambda_1$
		Planarity	$(\lambda_2-\lambda_3)/\lambda_1$
		Linearity	$(\lambda_1-\lambda_2)/\lambda_1$
		Surface Variation	$\lambda_3/(\lambda_1+\lambda_2+\lambda_3)$
		Sphericity	λ_3/λ_1
		Verticality	$1-\lvert\langle n_z, e_3\rangle\rvert$ (nz = (0,0,1))
	Moment	1st order 1st axis	$\sum_{i\in Neg(P)}\langle p_i - p, e_1\rangle$
		2nd order 1st axis	$\sum_{i\in Neg(P)}\langle p_i - p, e_1\rangle^2$
		1st order 2nd axis	$\sum_{i\in Neg(P)}\langle p_i - p, e_2\rangle$
		2nd order 2nd axis	$\sum_{i\in Neg(P)}\langle p_i - p, e_2\rangle^2$
	Height	Height Range	$Z_{\max} - Z_{\min}$
		Height Below	$Z_p - Z_{\min}$
		Height Above	$Z_{\max} - Z_p$
Our proposed new features	Directional height	Sliced Height Above (8 directions)	$[\, Z_{d1},\ Z_{d2},\ Z_{d3},\ Z_{d4},\ Z_{d5},\ Z_{d6},\ Z_{d7},\ Z_{d8}\,]$ Where $Z_{di} = Z_{p1} - Z_{p2}$
	DoN	Norm of DoN	$norm(\Delta n_d(p, P_{l\_i}, P_{l\_0}))$

Difference of Normal (DoN) is an arithmetic multi-scale operator for evaluating the geometric properties of a point cloud (Ioannou, 2012). Here, the term “scale” indicates the size of the radius used for normal estimation. It is defined as:

$$\Delta n_d(p, r_l, r_s) = \frac{n_l(p, r_l) - n_s(p, r_s)}{2} \qquad \textbf{(Eq 2-3)}$$

Where p is the given point

$n_l(p, r_l)$ is the normal estimated in a large radius r_l

$n_s(p, r_s)$ is the normal estimated in a small radius r_s

Surface normal estimation is dependent on the neighbors located in a sphere defined by radius r. In this paper, r_l is replaced by the downsampled fixed number of nearest neighbors at a larger scale and r_s is replaced by the downsampled fixed number of nearest neighbors at a smaller scale. Thus, the DoN based on the fixed number of nearest neighbors and the scale used for selecting neighbors are defined as follows:

$$\Delta n_d(p, P_l, P_s) = \frac{n_l(p, P_l) - n_s(p, P_s)}{2}$$ **(Eq 2-4)**

Where P_l represents a large-scale fixed number of neighbors

P_s represents a small-scale fixed number of neighbors

Hence, the change of scales for picking up nearest neighbors to compute the DoN can reflect the properties of the geometric shape and size of objects. For a perfect plane, the DoN is a zero vector. For a planar segment, the values of DoN for most points are near the zero vector. The histogram of the norm of DoN reveals the effectiveness of DoN for distinguishing between the objects having planar surfaces (such as buildings and roads) and those without regular geometric shapes (such as trees and bushes). Here the norm of a vector Δn_d is defined as:

$$norm(\Delta n_d) = \sqrt{(\Delta n_d.x)^2 + (\Delta n_d.y)^2 + (\Delta n_d.z)^2}$$ **(Eq 2-5)**

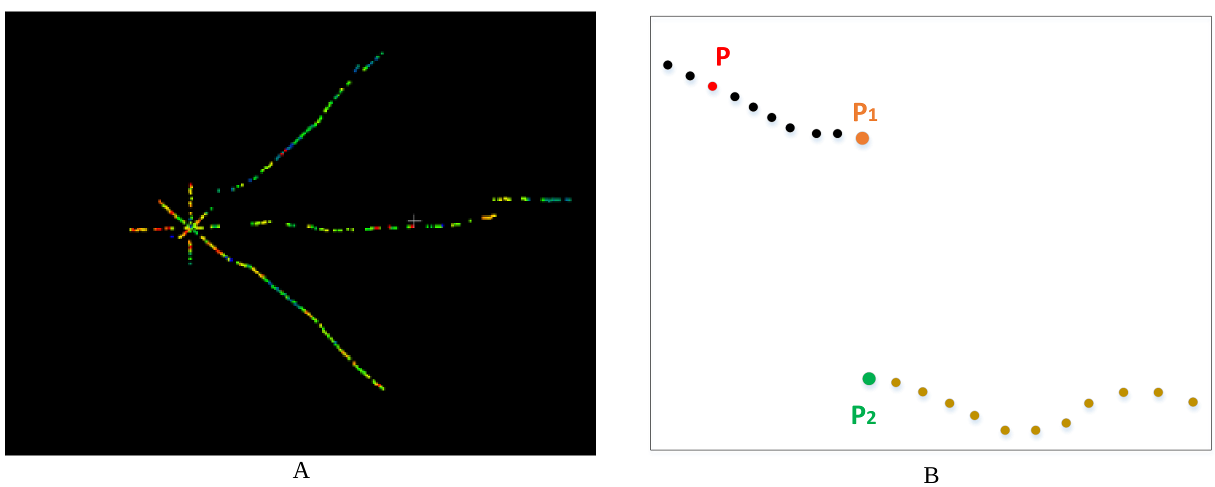


Figure 2-2 Illustration of "directional height above" feature in 8 directions

In Figure 2-3, an example is given to show the characteristics of the DoN for different types of objects in three different scales of r_s and r_l. The values of radius r_s and r_l are 0.5 and 1 meter, 0.5 and 1.5 meters, and 1 and 2 meters, respectively. In a point cloud of a building wall, over 98% of points fall in the range of the norm of DoN between 0 and 0.18 while most points have a greater value for a tree. This example reveals that the norm of DoN calculated between normals estimated using downsampled neighbors at different scales is effective for semantic segmentation of point clouds.

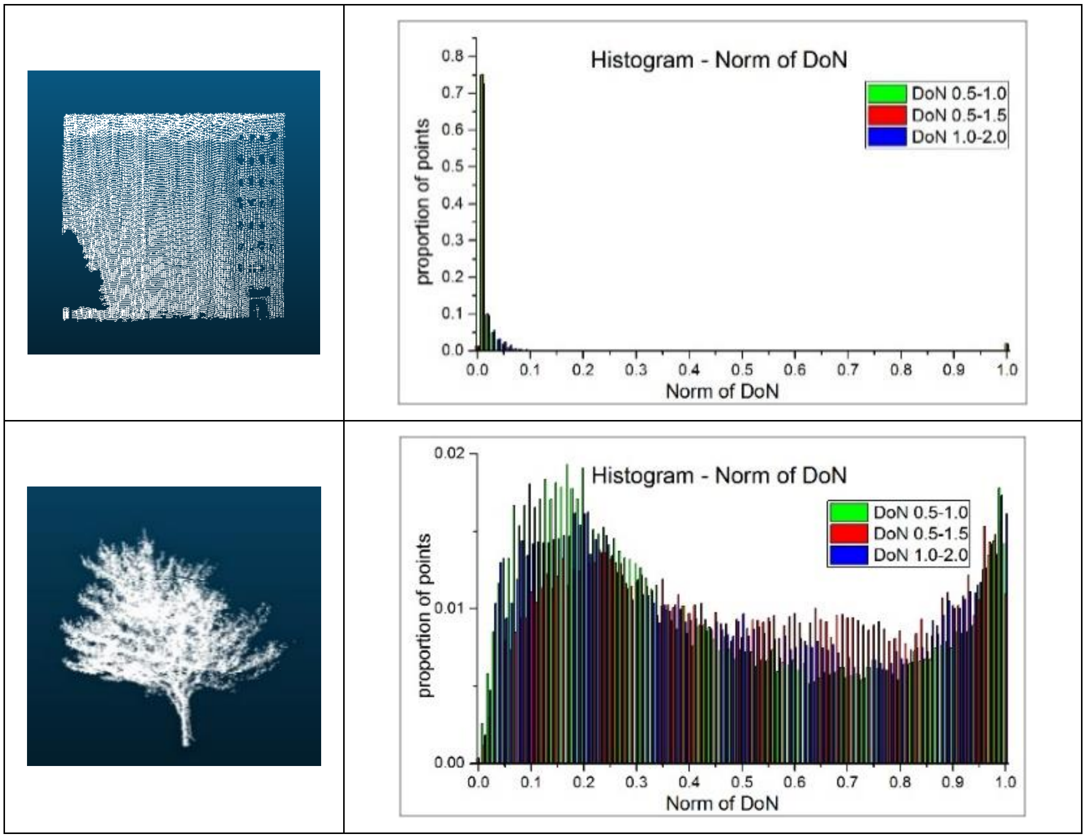


Figure 2-3 Histogram of the norm of DoN for distinguishing different objects.

2.6 Random Forest for Pointwise Semantic Segmentation

Random forest (Breiman, 2001) is composed of a collection of decision trees constructed using random features sampled independently. Each tree is trained on the training set based on bootstraps that creates a random resampling on training set itself, and random features are selected to create trees (Svetnik, 2003). The prediction is decided by aggregating the predictions of decision trees. Each node in a binary decision tree represents a feature selected for splitting samples into two classes. Gini impurity measures how well a potential split is in this node (Menze, 2009). The formula of Gini impurity is:

$$Gini(m) = 1 - \sum_{i=1}^{C} (p_i)^C \quad \textbf{(Eq 2-6)}$$

Where $p_i = n_k/n$ is the fraction of n_k samples from C classes out of the total of n samples at node m.

The multi-scale features defined in the previous section are organized as a features vector that combines features obtained in different scales. The feature vector is produced on each point. The feature vector represents the learnable variables of objects. Then the feature vectors are input into machine learning classifier for learning the parameters for classification from the training set. Similarly, the feature vectors calculated from the testing set are used in the semantic segmentation on the testing set for the evaluation of the performance of the learned classifier. Generally, the precision, recall, and F1-Score are calculated to compare the performance of the classifier.

We choose a Random Forest classifier for pointwise semantic segmentation because it is straightforward to deal with multi-class problems and it is easy to parallelize its implementation. It demonstrated good results on large-scale point clouds in a reasonable time (Hackel, 2016; Weinmann, 2015). We use the random forest algorithm in Scikit-learn library with Gini-impurity (Menze, 2009) as the splitting criterion. In our application, the density of point clouds is uneven, and it has high density on the ground. Due to occlusion, the scanning angle and the viewpoint of the scanner, some parts of objects are missing or have low density. Thus, the uneven density of points leads to a distribution of class labels that do not conform to reality, which affects the training of the classifier parameters. For decreasing this negative effect, the dataset is downsampled with an appropriate resolution. After downsampling, the dataset better represents the true distribution of classes in point clouds. In fact, the high density of points in the local area is not better than the even point density because it is difficult to reflect the geometric properties in a small range with dense points. Considering the computation efficiency, the downsampled training set is economic to fit the capabilities of memory and to get the classification done in a reasonable time. In addition, the classifier trained on the point cloud with even density and reasonable resolution has good generalization capabilities.

2.7 Experiments and Results

For the first experiment, a mobile LiDAR dataset is scanned at Laval University campus by a Terrapoint Titan mobile LiDAR system. The average point spacing in the point cloud is 0.089m. The point density is approximately 130 points/m2. A higher density of points is observed on the roads. Due to occlusions, scan angle, and objects properties, the point density is non-uniform and objects are incomplete in some parts of the point cloud. In the LAS files, the outlier points are cleaned, and moving objects and noisy points are removed from the raw dataset.

In addition, we have carried out the second experiment with an airborne LiDAR dataset from Montreal area. The point cloud contains flat urban terrain and changing topography following both sides of a railway. In the point cloud, there are buildings, vegetation, bridges, ground, and other object classes (e.g., power lines, cars, poles, etc.)

All algorithms are implemented in C++ in QT with Point Cloud Library for computing features and scikit-learn for classification using random forest classifier. All experiments are run on a laptop with Intel Xeon E3-1505 v5 CPU (quad-core, 2.8GHz) and 48 GB of RAM. The process of computing features is parallelized across the available CPU cores. The training of the model and the classification step are set to parallel as well.

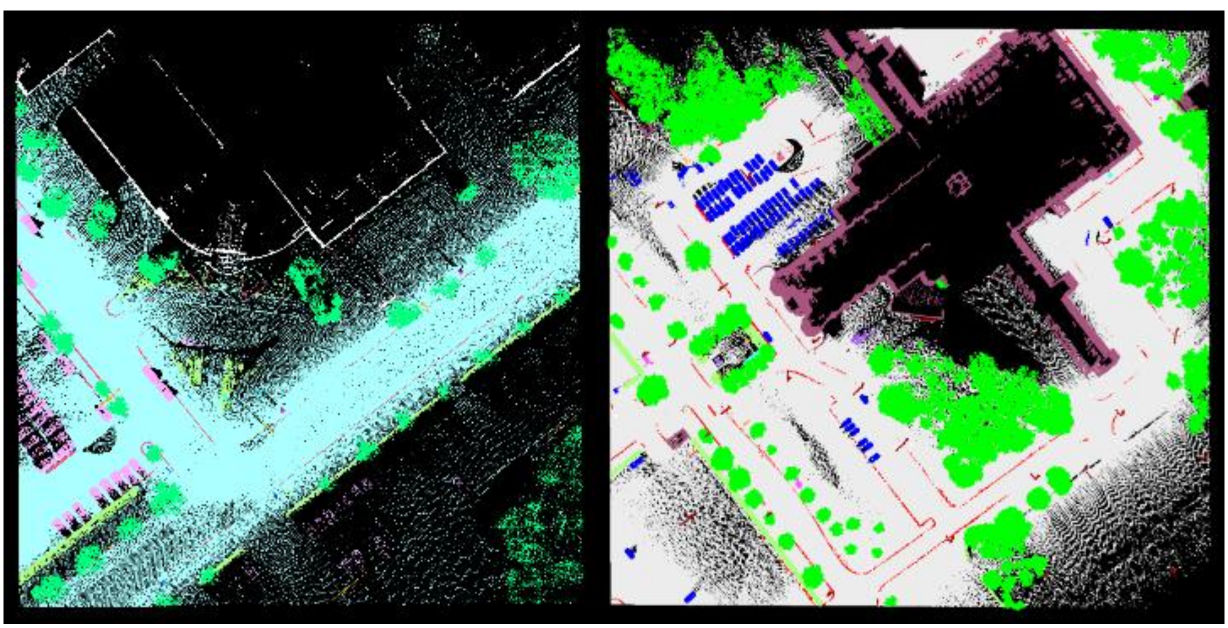
2.7.1 Experiments on Mobile Terrestrial LiDAR Point Cloud

Based on the proposed pointwise segmentation method, the features of each point are composed of features derived from multi-scale neighbor selection. We chose 8 scales (0.1, 0.2, 0.4, 0.8, 1.6, 3.2, 6.4 and 12.8 (meters)) for downsampling point clouds to calculate the features at each scale. The first scale is computed based on the average point density of point clouds. Here we consider the first scale to be slightly greater than the value of average point density. Then the DoN is computed as the difference between the normal estimated at the smallest scale and the normals at other larger scales. All the features are combined as a feature vector for each point. When the feature vectors of points are extracted, they are input into a random forest classifier to train the classification model. To do so, we first need to have a training set that contains the defined classes of objects for semantic segmentation. Based on this training set, other raw point clouds are classified using the trained model. The dataset in Figure 2-4(B) is chosen as the training set to train the model and the dataset shown in Figure 2-4(A) for testing. In the training set, there are classes of objects such as ground, bushes, trees, buildings, cars, curbs, light poles, sign poles, traffic indicators, benches, people, bus stations, etc. However, the points representing traffic indicators, benches, people and bus stations are low in proportion compared to the other object classes. In the testing dataset, there is a similar distribution of the objects.

We have defined 50 trees and Gini index as the splitting criterion to train the random forest classifier. Then the trained model is used on the testing dataset presented in Figure 2-4(A). The results of the test are presented in Table 2-2. The classification results of the testing dataset are presented in Figure 2-5. The analysis of the results reveals that in the case where objects are too close to each other and have similar geometric properties (such as trees and bushes), or are absent in training set, the classification is not very efficient. For instance, in the training set, bushes and trees are located close to each other. In the testing set, some parts of the bushes are misclassified into the tree class. Also, when the point cloud is downsampled for calculating the feature vectors, the geometric properties of curves are not clear extracted. As the curved walls do not occur in the training set, the curved parts of the building in the given data set are misclassified into tree class. Additionally, the density of points for traffic indicators, benches, and people is not high enough and the numbers of instances of these classes are all less than 3, which is not enough to make the classifier learn.

Table 2-2 Quantitative results of testing on mobile LiDAR point cloud (Precision (P), Recall (R), F1-Score (F1))

Classes	Our results (%)			Results based on features in (Hackel, 2016) (%)		
	P	R	F1	P	R	F1
Ground	93.92	99.88	96.81	93.85	99.90	96.78
Bush	45.31	50.57	47.80	39.27	49.84	43.92
Tree	78.81	98.59	87.60	80.51	96.61	87.83
Building	88.97	71.38	79.21	84.90	70.49	77.03
Car	93.46	45.89	61.56	95.07	45.57	61.61
Curb	72.89	3.34	6.39	77.42	2.81	5.42
Light pole	97.94	36.52	53.20	97.40	38.00	54.67
Sign pole	49.37	15.29	23.35	38.69	18.68	25.19
Traffic indicator	0	0	0	0	0	0
Bench	0	0	0	0	0	0
People	0	0	0	0	0	0
Bus station	0	0	0	0	0	0
Overall	90.29	90.43	88.92	90.24	90.16	88.74



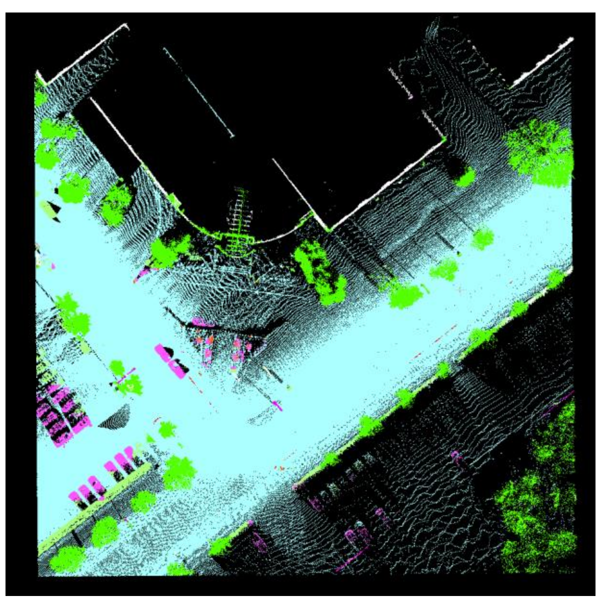
A B

Figure 2-4 Dataset for testing (A) and for training the classification model (B)

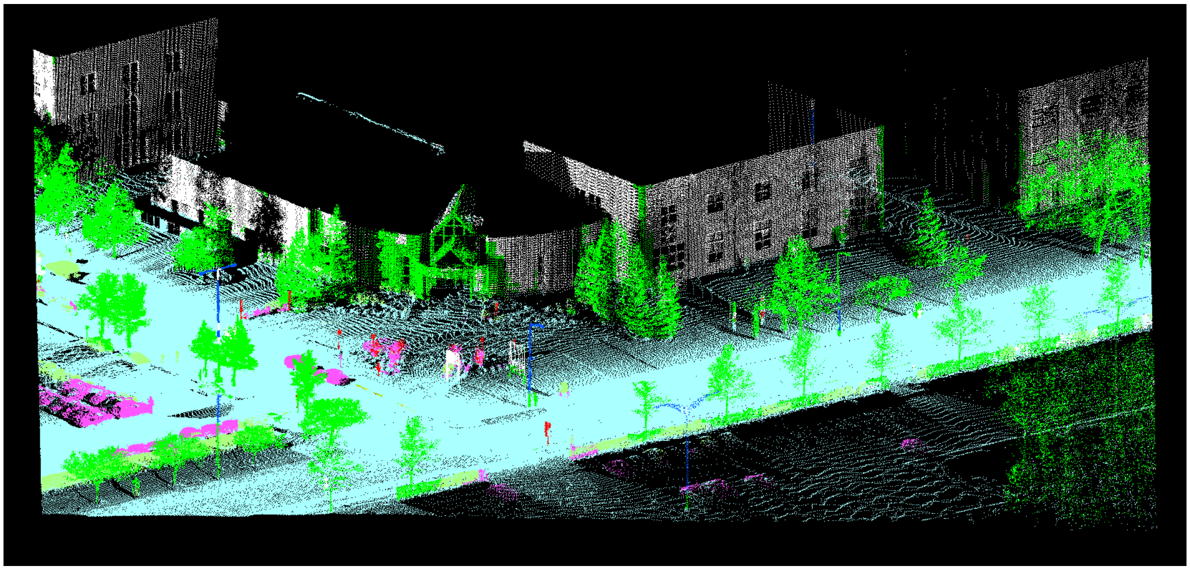
2.7.2 Experiments on Airborne LiDAR Point Cloud

The airborne LiDAR point cloud of urban areas for the experiment contains ground, vegetation, building, bridge, power line, tower, fence, car, and pole. In this experiment, we classify point cloud into six classes: ground, low vegetation, middle vegetation, high vegetation, building, and others. The bridges are classified into building class. The rest of the objects are given as other classes, including power lines, cars, fences, towers, and poles near to railway. In Figure 2-7, the left part is chosen as the training set and the right part for testing. In the training area, there are bridges and tunnels in the ground class. The testing area contains the railway environment, and there is a changing topography on both sides of the railway (Figure 2-6). In contrast, in the training area, the topography is relatively smooth and flat.

We chose seven scales (0.2, 0.4, 0.8, 1.6, 3.2, 6.4 and 12.8 (meters)) for downsampling point clouds to calculate the features at each scale. The first scale is decided as 0.2 due to the average point density of airborne LiDAR point clouds is near to 0.2 meters. After training the classification model from the training area of the point cloud, we compare our results and the result based on the features in (Hackel, 2016) (Table 2-3). Our proposed features for semantic segmentation of airborne LiDAR point clouds have good performance in building class and high vegetation class. As shown in Figure 2-8, our results are better than the results based on features in (Hackel, 2016) in building classes. However, we can still see some misclassifications in the results. As shown the results in Figure 2-8(A), some points in the central part of the building roof are misclassified as ground class.



A



B

Figure 2-5 Classification result on the testing point cloud (A) and its 3D view (B)

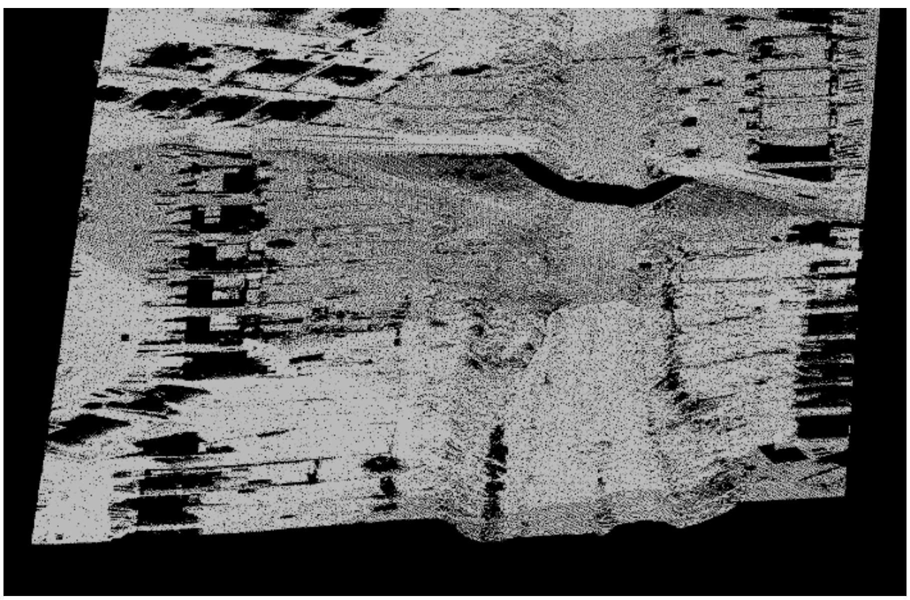


Figure 2-6 3D view of points for creating topography in the testing area

Table 2-3 Quantitative results of testing on airborne LiDAR point cloud (Precision (P), Recall (R), F1-Score (F1))

Classes	Our results(%)			Results based on the features in (Hackel, 2016) (%)		
	P	R	F1	P	R	F1
Ground	96.74	98.99	97.85	94.26	99.14	96.64
Low vegetation	83.29	1.13	2.23	71.67	1.22	2.39
Middle vegetation	75.84	10.09	17.80	75.04	11.88	20.52
High vegetation	96.96	89.59	93.13	97.08	84.4	90.26
Building	94.70	90.28	92.44	91.44	75.52	82.72
Others	43.26	70.99	53.67	42.54	71.12	53.24
Overall	93.27	92.27	91.47	90.95	90.01	89.14

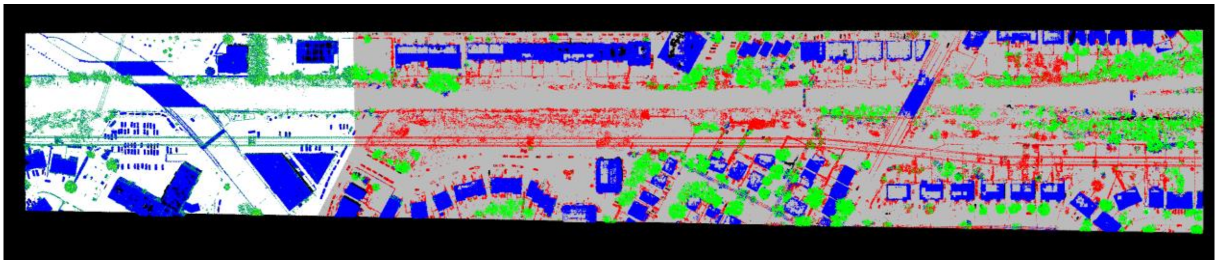
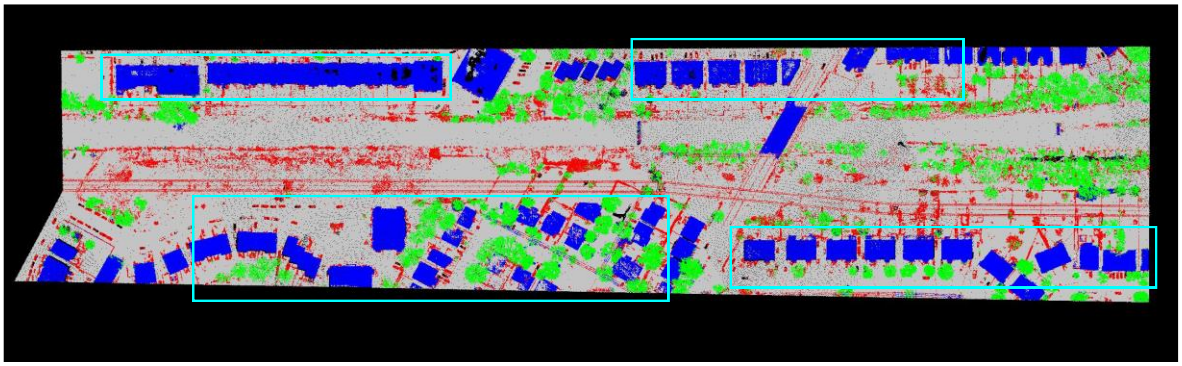
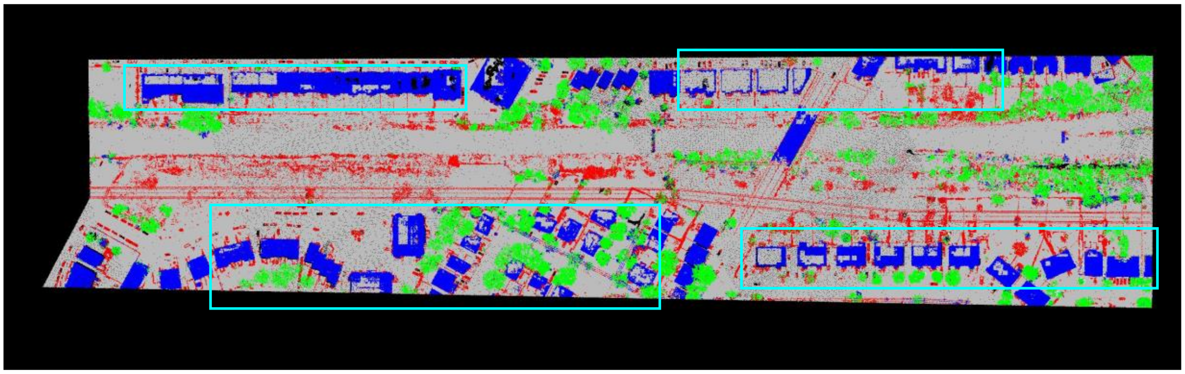


Figure 2-7 Datasets for training (left) and testing (right)



A



B

Figure 2-8 Comparison of semantic segmentation results of airborne LiDAR point cloud. (A) our result and (B) result based on features in (Hackel, 2016)

2.7.3 Discussion

In this experiment, the proposed features help to improve the overall semantic segmentation of an urban scene from mobile terrestrial LiDAR point clouds. More specifically, there is an obvious improvement of precision in the building class. For semantic segmentation of airborne LiDAR point cloud, our proposed new features are effective to ground, building and low vegetation classes. In the overall semantic segmentation, our results have 2.26% improvement from the comparison of recall between ours and Hackel's results. However, due to the unbalance of object classes and the limited number of examples, the bridge class is not learned from training sets. In this case, a greater data set can help to produce more examples in the training step. In addition, the computation time for semantic segmentation of airborne LiDAR point clouds using our method is about 10 minutes/million points. In general, more features require more computation time. In our work, the computation of directional height difference is easy to be parallelized based on the downsampling of point clouds. But the steps of downsampling and normal estimation are not parallelized. There is still a space to improve the computation time if the downsample and normal estimation are done using parallel computation on CPU or GPU.

2.8 Conclusion and Future Work

In this paper, we have proposed an improvement to previously proposed methods for semantic segmentation by adding features derived from Difference of Normal (DoN) and "directional height above" neighbors for semantic segmentation of mobile and airborne LiDAR point clouds. The proposed features allow improving semantic segmentation of mobile and airborne point clouds in urban scenes. We use a random forest classifier for pointwise segmentation of point clouds. After comparing our results and the results based on features in (Hackel, 2016), the newly proposed features produce slightly improved semantic segmentation results of vegetation and building classes in mobile LiDAR point clouds. However, there are significant improvements on the vegetation and building classes in the semantic segmentation of airborne LiDAR point clouds. As future work, we plan to integrate other features that can be extracted from supplementary data sources into the proposed approach that will allow to further improve semantic segmentation of a LiDAR point cloud.

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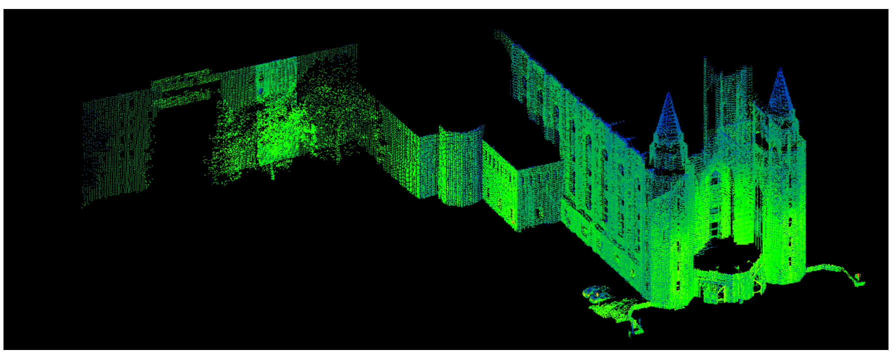
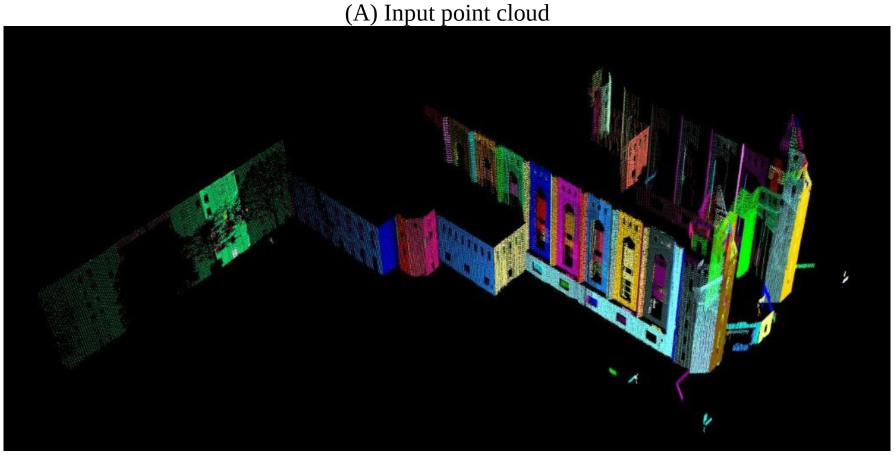
Introduction of Article

Towards Automatic Segmentation of Buildings with Complex Structure from LiDAR Point Clouds

Following the work have done in Chapter 2, our work contributes to automatic semantic segmentation of airborne and mobile terrestrial LiDAR point clouds. In Chapter 3, CAD-like segmentation aims to identifying object components as shown in the following figure where points with same color represent a component of the building. In general, CAD-like segmentation segment the points belonging to an object into small segments according to the geometric properties. Semantic segmentation of point clouds helps to reduce the difficulties of CAD-like segmentation of objects directly from point clouds of complex urban scenes. The combination of semantic segmentation and CAD-like segmentation all contribute to creating semantically enriched 3D models of objects.



(A) Input point cloud



(B) The result of CAD-like segmentation

Figure V the expected work in CAD-like segmentation

In chapter 3, an article “Towards Automatic Segmentation of Buildings with Complex Structure from LiDAR Point Clouds” is presented. The purpose of this article is to solve the problems of the selection of segmentation algorithms and their parameters for specific types of objects, and the problems of over-segmentation and under-segmentation in the CAD-like segmentation of objects with complex structures. In this article, first, automatic pointwise semantic segmentation has done in Chapter 2 is used to classify points into several classes of object types. Then, segmentation algorithms for buildings with complex structures are designed for CAD-like segmentation of objects according to the smoothness of the surface of objects and their geometric properties obtained by classifying surface types using Support Vector Machine classifiers. Finally, we proposed the algorithms for decreasing the cases of over-segmentation and under-segmentation. The experiment shows that our proposed algorithm is robust to segment complex buildings.

CHAPTER 3 Towards Automatic Segmentation of Buildings with Complex Structure from LiDAR Point Clouds

Xu-Feng XING, Mir Abolfazl Mostafavi, Geoffrey Edwards, Nouri Sabo

3.1 Résumé

La segmentation automatique des nuages de points observée dans une scène urbaine complexe en 3D est un défi difficile pour l'automatisation de la modélisation 3D à partir de nuages de points LiDAR. Dans cet article, nous présentons une segmentation semblable à la CAO de bâtiments à structure complexe dans une scène urbaine à partir de nuages de points Lidar. Tout d'abord, la segmentation sémantique par points est choisie pour classer les nuages de points de scènes urbaines afin de séparer les points appartenant aux bâtiments. Pour réaliser une segmentation semblable à la CAO de bâtiments à structure complexe, le type de surface (surfaces lisses et non lisses) identifié sur la base des nouvelles fonctionnalités proposées permet de choisir les paramètres appropriés pour les algorithmes de segmentation. Nous avons également développé un algorithme pour surmonter les cas de la sous-segmentation et la sur-segmentation. Enfin, les résultats des expériences montrent que la solution proposée permet de segmenter efficacement des bâtiments aux structures complexes.

3.2 Abstract

Automatic segmentation of point clouds observed in a 3D complex urban scene is a challenging issue for the automation of 3D modeling from LiDAR point clouds. In this paper, we present a CAD-like segmentation of buildings with complex structure in an urban scene from LiDAR point clouds. First, pointwise semantic segmentation is chosen to classify point cloud of urban scenes for separating the points belonging to buildings. For realizing CAD-like segmentation of buildings with complex structure, surface type (smooth and unsmooth surfaces) identified based on proposed new features helps to choose the appropriate parameters for segmentation algorithms. We also developed an algorithm to overcome under-segmentation and over-segmentation cases. Finally, the results of experiments show that the proposed solution can efficiently segment buildings with complex structures.

Keywords: automatic segmentation, buildings with complex structure, CAD-like segmentation, LiDAR point cloud

3.3 Introduction

With the rapid development of LiDAR technologies, airborne and terrestrial LiDAR datasets are widely used as an important source of geospatial information for various applications ranging from 3D mapping to urban planning, land surveying, building reconstruction, 3D city modeling and digital heritage management (Yang, 2013). The LiDAR data processing and modeling steps take tremendous time and operator efforts compared to the data acquisition step. According to experts in the field, the time spent on data processing work (increased by 200-300%) is out of proportion compared to the time spent on surveying field work (cut down by 80-90%) (Knaak, 2012). For some applications such as evaluating sea cliff changes (Young, 2010), monitoring subsidence around coal mines (Froese, 2008), and detecting transport network obstructions by comparing LiDAR data before and after disasters to shorten the time of reaching disaster sites (Kwan, 2010), efficient data processing significantly decreases the time of evaluation, monitoring, and emergency response. In addition, in some real-time applications such as self-driving cars, which navigate themselves by integrating LiDAR scanners to observe the surrounding areas (Fisher, 2013), the necessity of automated information extraction, including segmentation and object recognition, is essential to make on-the-fly decisions for a secure navigation. Furthermore, dynamic environment maps and real-time semantic 3D object maps are important prerequisites in motion planning for robots self-navigation as well (Rusu, 2010).

Automatically deriving semantic information about objects and automatically creating CAD-like geometric representations of objects from point clouds are both difficult but crucial steps for the automatic creation of geometric 3D models (Hackel, 2016). Essentially, CAD-like segmentation is the process of partitioning a point cloud into groups with homogeneous properties where all points belonging to a group have the same meaningful label (Awwad, 2010; Rabbani, 2006). For instance, points belonging to the same geometric primitive can represent the components of man-made objects. Segmentation methods for airborne LiDAR data have been developed for classification (Filin, 2002b; Lodha, 2006; Moussa, 2010b; Peng, 2011; Smeeckaert, 2013), object extraction (Keqi, 2003; Opitz, 2006), 3D building roof segmentation (Awrangjeb, 2014; Cheng, 2013; Dorninger, 2007; Vosselman, 2001), vegetation detection (Erikson, 2004) and analysis. Terrestrial LiDAR data provides more detailed near-ground information of 3D scenes, which are typically very dense, and where the types of objects are very diversified (Tang, 2010). The segmentation methods and algorithms for terrestrial LiDAR data are different. Examples include road detection (Xu, 2017; Yu, 2015) and building reconstruction (Wang, 2016b) from mobile LiDAR data. However, there are several challenges related to the automatic segmentation of LiDAR point clouds due to noise, uneven density, and occlusions in point clouds (Nguyen, 2013). In addition. over-segmentation, under-segmentation, and non-segmentation cases could occur in the segmentation of a complex urban scene due to the inappropriate parameter selections of segmentation algorithms.

In this paper, we present a CAD-like segmentation algorithm for building with complex structures in an urban scene. The features for identifying surface types (smooth and unsmooth) are defined to help to decide appropriate parameters of segmentation algorithms. Based on the defined features for classifying surface type and SVM classifier, the surface type is helpful to decide the appropriate parameters for the segmentation of buildings with complex structure. We also propose a segmentation algorithm to overcome the over-segmentation and under-segmentation caused by the sensitivity of segmentation algorithm parameters.

The remainder of this paper is structured as follows: Section 2 reviews related work in the field of automatic segmentation of point cloud data. Sections 3 presents the proposed solutions in detail. Section 4 presents a case study, the obtained results, and their analysis. Finally, Section 5 concludes this work and presents some perspectives on future work.

3.4 Related Work

There are several categories of segmentation algorithms for terrestrial LiDAR point clouds including clustering methods, region growing methods, model fitting methods, knowledge-based methods and machine learning algorithms for segmentation. Although much effort has been made to improve the segmentation methods for individual types of objects, less effort has been made on the automation of the segmentation process based on semantics and qualitative information combined with geometric information extracted from point clouds.

Clustering algorithms are powerful tools to group data into homogeneous patterns. In this approach, clusters are determined based on similar properties, such as distance, density (Rodriguez, 2014), curvature, etc. The clustering methodology provides a general and flexible way to accommodate spatial relationships and attributes for point cloud segmentation, as presented in Filin (Filin, 2002a) and Biosca (Biosca, 2008). Based on the principle of the traditional clustering algorithm K-means (MacQueen, 1967), some clustering algorithms (Lu, 2016; Yamauchi, 2005; Zhang, 2008) have been explored to segment point clouds. However, for clustering algorithms, determining an appropriate criterion to cluster points is still a challenging issue.

Region growing methods require the identification of seeds to recognize a surface and predefined criteria to expand the surface towards adjacent points. The criteria for growing a surface include information on the proximity of points, local planarity, smoothness (Rabbani, 2006; Vosselman, 2004) and curvature. Segmentation based on the smoothness criterion has a better effectiveness for complex surfaces than curvature-based methods. Additionally, region growing methods are used to segment smooth surfaces to find the points belonging to a segment (Pu, 2006b; Pu; Vosselman, 2004; Wang, 2011; Xiao, 2013) from point clouds. In summary, region growing methods are efficient to extract smooth surfaces, but they are sensitive to noisy data, the selection of the initial seed and the quality of the normal estimation, which could result in over-segmentation and under-segmentation problems.

The model fitting methods are based on matching geometric primitives. The points that fit the mathematical representation of predefined models are grouped as one segment (Awwad, 2010). However, the relationship between segmentation and surface fitting is regarded as the problem of "chicken and egg" (Shah, 2006; Várady, 1997), as the extraction of prior information from point clouds and the selection of predefined models are dependent on each other. RANdom SAmple Consensus (RANSAC) (Fischler, 1981) and Hough transform (Hough, 1962) algorithms are typically used in model fitting methods. However, considering the sensitivity of the segmentation parameters, RANSAC (Schnabel, 2007) is more efficient and commonly used because it has the great advantage of being robust, even in the presence of noise in datasets (Tarsha-Kurdi, 2007a). Additionally, several extensions, including MLESAC (Maximum Likelihood Estimation SAmple and Consensus) (Torr, 2000), MSAC (M-estimator SAmple and Consensus) (Torr, 1997), PROSAC (Progressive Sample and Consensus) (Chum, 2005), have been implemented in the Point Cloud Library (Rusu, 2011). Model fitting methods are fast and robust to extract geometric shapes from point clouds with noise. However, RANSAC algorithms have non-negligible shortcomings, such as spurious planes produced from point clouds (e.g., from stairs structures) (Awwad, 2010). They do not work well in complex shape detection from incomplete point clouds caused by occlusion and uneven density.

Knowledge-based methods and machine learning algorithms have also been explored in segmentation from point clouds. For example, Boochs et al. (Boochs, 2011), Hmida et al. (Hmida, 2012b) and Truong et al. (Truong, 2013a) used semantic knowledge in all point cloud processing stages for object detection. They built the knowledge module, the algorithm selection module and the semantic qualification engine for detecting objects. Lu et al. (Lu, 2016) presented a novel hierarchical clustering algorithm based on pairwise linkage to cluster any dimensional data. This algorithm can be applied in the segmentation process of airborne, terrestrial and mobile LiDAR point clouds. However, the results are not perfect on the edges (e.g., corners and ridges of the roofs) of buildings. Additionally, the multi-scale features for dealing with varying point density (Hackel, 2016) are calculated for semantic segmentation using a random forest classifier, which is the supervised pointwise classification of point clouds. Other solutions based on deep learning for semantic segmentation include Pointnet (Qi, 2017), PointCNN (Li, 2018), which all require a large number of training datasets to train the models.

In summary, in a complex 3D urban scene composed of various types of objects, segmentation algorithms based only on geometric properties have several limitations. These include the application of non-appropriate parameters of segmentation algorithms for specific object types in the automatic segmentation process. Having semantic information on the 3D urban scene to be processed may help to overcome these limitations. Hence, for achieving CAD-like geometric representation of buildings with complex structures in an urban scene from point clouds, integrating semantic information of object properties is promising to improve the segmentation results of buildings with complex structure even in the case of the incompleteness and uneven density in point clouds.

3.5 Method

Knowing the geometric properties of objects is an essential step in the automatic segmentation process of a point cloud. We may use a specific segmentation algorithm to ensure the effectiveness of CAD-like segmentation of objects according to their geometric properties. When the surface type of objects, such as smooth or unsmooth, is obtained, the selection of suitable segmentation algorithms and their appropriate parameters is conducted. The segmentation of buildings with complex structures from point clouds in an urban scene is divided into the following steps:

- Pointwise semantic segmentation. Each point is classified according to multi-scale features extracted from point clouds. After semantic segmentation, the points belonging to buildings are separated (section 3.5.1).
- Classify surface type (smooth and unsmooth). The features for distinguishing smooth and unsmooth surface are identified and then a group of points can be classified into the smooth and unsmooth surface. (section 3.5.2)
- Segmentation algorithm for decreasing over-segmentation results. An algorithm based on geometric reasoning is proposed to decrease the over-segmentation results, and the appropriate parameters are defined according to the surface type. (section 3.5.4).

3.5.1 Pointwise Semantic Segmentation

For a large-scale urban scene, the extraction of multi-scale features from dense point clouds requires huge computation capabilities with the given range of selecting neighbors. Decreasing the point density in a large range is necessary to balance computation cost and time. The strategy of downsampling (Brodu, 2012;

Hackel, 2016) point clouds makes it possible to select a fixed number of nearest neighbors for different scales. The point cloud is downsampled by generating a pyramid of scales using different voxel size. Based on the normal estimation in a point cloud, the features derived based on normal estimation (Gross, 2006; Hackel, 2016; Wang, 2015) at different scales are calculated (as shown in Table 3-1).

Table 3-1 Features derived from eigenvalues, moments around eigenvectors and spatial elevation

Covariance	Sum	$\lambda_1+\lambda_2+\lambda_3$
	Omnivariance	$\sqrt[3]{\lambda_1\cdot\lambda_2\cdot\lambda_3}$
	Eigenentropy	$-\sum_{i=1}^{3}\lambda_i\cdot\ln(\lambda_i)$
	Anisotropy	$(\lambda_1-\lambda_3)/\lambda_1$
	Planarity	$(\lambda_2-\lambda_3)/\lambda_1$
	Linearity	$(\lambda_1-\lambda_2)/\lambda_1$
	Surface Variation	$\lambda_3/(\lambda_1+\lambda_2+\lambda_3)$
	Sphericity	λ_3/λ_1
	Verticality	$1-\lvert\langle n_z, e_3\rangle\rvert$ (n_z = (0,0,1))
Moment	1st order 1st axis	$\sum_{i\in Neg(P)}\langle p_i-p, e_1\rangle$
	2nd order 1st axis	$\sum_{i\in Neg(P)}\langle p_i-p, e_1\rangle^2$
	1st order 2nd axis	$\sum_{i\in Neg(P)}\langle p_i-p, e_2\rangle$
	2nd order 2nd axis	$\sum_{i\in Neg(P)}\langle p_i-p, e_2\rangle^2$
Height	Height Range	$Z_{\max}-Z_{\min}$
	Height Below	$Z_p-Z_{\min}$
	Height Above	$Z_{\max}-Z_p$
Our proposed features	Height Above Sliced (8 directions)	[Z_{d1}, Z_{d2}, Z_{d3}, Z_{d4}, Z_{d5}, Z_{d6}, Z_{d7}, Z_{d8}] Where $Z_{di}=Z_{p1}-Z_{P2}$ p1 and p2 are neighboring endpoints of smooth line segments with sharp change
	Norm of Difference of Normal (DoN) (Ioannou, 2012)	$norm(\Delta n_d(p, P_{l\_i}, P_{l\_0}))$, where $\Delta n_d(p, P_l, P_s)=(n_l(p, P_l)-n_s(p, P_s))/2$, and $norm(\Delta n_d)=\sqrt{(\Delta n_d.x)^2+(\Delta n_d.y)^2+(\Delta n_d.z)^2}$ $n_l(p, P_l)$ is the normal estimated using neighbors in a large scale P_l, and $n_s(p, P_s)$ is the normal estimated using neighbors in a small scale P_s.

Based on above features, we choose Random Forest classifier for pointwise segmentation because it is straight-forward to deal with multi-class problems and is easy to parallelize in its implementation. It demonstrated good results on large-scale point clouds in a reasonable time (Hackel, 2016; Weinmann, 2015). We use the random forest algorithm in Scikit-learn library with Gini-impurity as the splitting criterion. The features calculated on different downsampled point cloud are combined together as the features for semantic segmentation. Considering the computation efficiency, the downsampled training set is economic to fit the capabilities of memory and to get the classification done in a reasonable time.

3.5.2 Features for Segmenting Object Components

Surfaces may be classified as smooth and unsmooth. If a small smoothness threshold is used to segment an unsmooth surface, it may lead to the over-segmentation results. To avoid this problem, we first identify the surface type from the point cloud after a semantic segmentation has been conducted. The characteristics of the surface normal of smooth and unsmooth surfaces in the point cloud can be described by the differences between the normal of a point and that of its nearest neighbors. Similarly, the difference between the curvature on a point and that of its nearest neighbors can help to determine the surface type. We define the average angle ($\overline{a_i}$) between the normal of points and the normal on their K nearest neighbors and the average curvature ($\overline{c_i}$) of points to characterize the smoothness of a surface.

$$\overline{a_i} = \frac{1}{k}\sum_{j=1}^{k}\cos^{-1}(n_i, n_j), \quad j \in neigh(i,k) \qquad \textbf{(Eq 3-1)}$$

$$\overline{c_i} = \frac{1}{k}\sum_{j=1}^{k}\left|c_i \text{-} c_j\right|, \quad j \in neigh(i,k) \qquad \textbf{(Eq 3-2)}$$

Following the estimation of the average angle between normals and the average curvature on each point in a point cloud, their respective histograms are generated separately. The angle between two normal vectors can vary between 0 and 180 degrees. In the histogram of the average angle, the interval is defined as 1 degree. Similarly, we choose a range between 0 and 0.1 to create the histogram of average curvature. In equations 5 and 6, we define k=8 to generate the histograms. The histograms of the examples of smooth and unsmooth surfaces are shown in Figure 3-1. In the histograms of smooth surfaces, the average angle between normals and the average curvature are located in a small range near zero. Compared to smooth surfaces, the average angle between normals and the average curvature in the histograms of unsmooth surfaces are distributed in a relatively larger range. The histograms of average curvature can also reveal information on the existence of curved surfaces in point clouds. In conclusion, the histograms of the average angle between normals and of average curvature of surfaces formed by a set of points in a point cloud can help to characterize the shape and the smoothness of a surface.

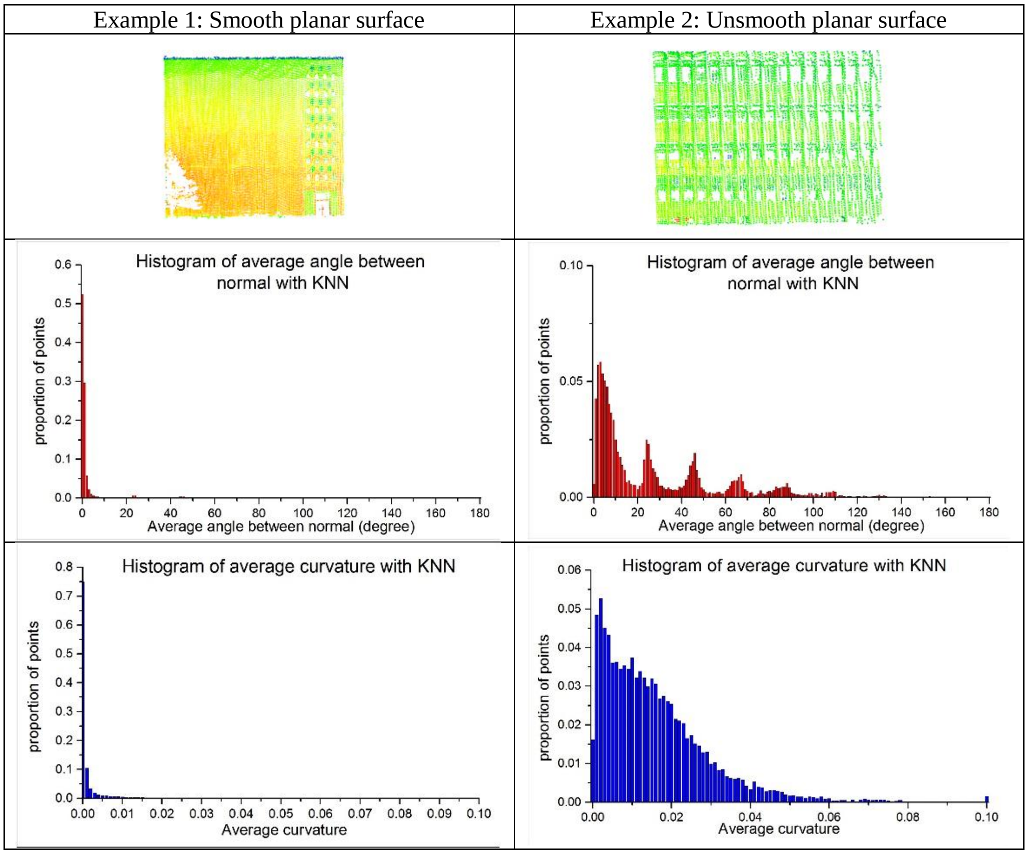


Figure 3-1 Histograms of average angle between normals and average curvature for smooth surfaces.

3.5.3 SVM for Surface Type Classification

Surface types indicate the geometric properties of objects. In such a context, we propose to use the Support Vector Machine (SVM) algorithm to classify surface types. SVMs have a rigorous theoretical foundation and have a good performance on high dimensional data in practice (Roobaert, 1999). SVMs are linear classifiers that find a hyperplane to separate two classes of data. They can efficiently perform on non-linear classification problems using kernel functions (linear, polynomial, sigmoid, Gaussian RBF) that implicitly map inputs into high-dimensional feature spaces. In previous studies, SVMs were used to learn 3D geometric primitives (Rusu, 2008a) and to evaluate local geometry at different scales (Brodu, 2012). Moreover, SVMs have a good performance on small scale training sets. Thus, we choose SVMs for classifying surface types from clusters of point clouds representing complex urban scenes.

We use the histograms of the average angle between normals and of average curvature between neighbors to construct a training set to train a SVM prediction model to classify the surface type (smooth or unsmooth). Each value on the vertical axis of the histogram is organized as the feature vector of a cluster in the training set. We use partially labeled clusters of point clouds as a training set to train the SVM parameters. Once the prediction model is trained, the histograms of the average angle between neighboring normals and of average curvature extracted from unlabeled surface in the point cloud are input into the model to classify the surface type. The classification results consist of the labels and the probabilities corresponding to these labels.

3.5.4 Segmentation Algorithm for Buildings with Complex Structure

As explained in the previous section, based on the SVM classification results, appropriate algorithms are chosen to segment buildings. However, most of the existing segmentation algorithms could result in under-segmentation, over-segmentation, and non-segmentation problems when they are used to segment point clouds from complex urban scenes. Due to the diversity of objects and their shape, an adapted algorithm should be designed for each object type with a specific shape. Here, we propose an adaptable algorithm framework to cope with the over-segmentation and under-segmentation problems of the shape-based segmentation, such as for planes, cylinders, spheres, and cones. For decreasing the over-segmentation and under-segmentation cases, a segmentation solution based on geometric reasoning is proposed. The solution balances these cases. The detailed descriptions of the segmentation steps are as follows:

Step 1: A region growing algorithm is used to segment the point cloud using an estimated smoothness threshold. First, the average of the $\overline{a_i}$ of the point cloud is calculated as the smoothness parameter for the region growing segmentation algorithm. Then, we classify the surface types of segmentation results based on the trained model. According to the surface type, the threshold θ_{th} is used to decide whether the iteration should continue. The θ_{th} threshold will not affect the final segmentation results but it is used to decrease the possibility of over-segmentation and under-segmentation cases (as shown in the results of Figure 3-4 and Figure 3-5).

Step 2: The RANSAC algorithm is used to detect planar segments with plane parameters from each planar segment obtained following the region growing segmentation step. For example, a specific planar segment gets parameters (a,b,c,d) to represent its plane equation $a_i x + b_i y + c_i z + d_i = 0$ with a normal vector (a_i, b_i, c_i).

Step 3: In the case of over-segmentation, we propose an algorithm based on geometric reasoning using the obtained planarity parameter based on the RANSAC segmentation algorithm. Parallel planar segments have parallel normal vectors. Coplanar segments have the same plane equation and can be combined in some cases to reduce the over-segmentation problem. The detailed steps are as follows:

Step 3.1: The parameters of the plane equation are used to merge planar segments to overcome the over-segmentation problem through the detection of coplanarity. For this purpose, based on the parameters of planar segments, the input planar segments are first classified into several sets P_c. In each set, there are some parallel planar segments. To obtain these sets, we choose the planar segment with the maximum number of points as a reference to decide if other segments are potentially parallel to it. If the angle between a planar segment and the reference segment is less than a given threshold, the planar segment is added to a new set. Consequently, the planar segments are separated into several sets with parallel planar segments $P_c = \{P_1, P_2, ..., P_n\}$. Here $P_i = \{C_1, C_2, ..., C_m\}$. In the subset P_i, planar segments are sorted by their number of points. We then select the segment with the maximum number of points $C_{\max}$. We choose planar segments C_j located near $C_{\max}$ within a distance threshold and combine them as a new segment C_{mix}. The RANSAC algorithm with a planar model is used to detect whether two planar segments are coplanar. It is also used to reallocate the points belonging to planar segments. If the planar segment with the maximum number of points is unchanged after applying the RANSAC algorithm, it indicates that these two planar segments should not be merged. If the planar segment with the maximum number of points has more points than the original $C_{\max}$, the two segments should be merged to create a new $C_{\max}$ and the C_j segment is deleted from P_i. This process is applied to all segments in P_i. After the loop has executed on all planar segments, P_c consists of new coplanar sets after the coplanar detection based on parallel sets. Finally, $P_c = \{P_1^{'}, P_2^{'}, ..., P_m^{'}\}$. The detailed steps are described as pseudocode in Figure 3-2 and Figure 3-3.

Step 3.2: Based on the results of step 3.1, the average orthogonal distance between points and planes is used as the criterion to decide whether two planar segments can be considered coplanar. Planar segments in P_i are processed to detect coplanarity. First, we select the cluster $C'_{\max}$ with a maximum number of points. Second, we determine whether other segments are coplanar to it. $OD(p_i, pl)$ represents the orthogonal distance of point p_i to plane pl. The average distance ($\overline{d}$) of points in a planar segment to a plane equation obtained from another planar segment is defined as:

$$\overline{d} = \frac{1}{n} \sum_{i=0,\, pi \in Cj}^{n} OD(p_i, pl) \qquad \textbf{(Eq 3-3)}$$

Here pl is the plane equation of planar segment $C'_{\max}$, C_j is the cluster in P_i. If $\overline{d} < d_p$, C_j is merged into $C'_{\max}$. Finally, when all the planar segments in P_i are detected, new planar segments are obtained after the detection of parallelity and coplanarity.

Figure 3-2 Parallelity detection algorithm.

```
Test parallelity of planar segments
Inputs:
Planar segments  produced by RANSAC  P = {C1,C2,..., Cn}
Angle threshold θTh
Initialize:
Parallel planes list  Ps = Ø
Sorted Planes by the number of points   P_sorted = Ø
Algorithm:
P_sorted = sort(P);
While(P_sorted≠ Ø) do
   Create parallel list temporary Pt_result;
   Cmax = P_sorted.begin();
   delete Cmax  from P_sorted;
   Pt_result.add(Cmax) ;
   for each left item in P_sorted do
      if   cos-1(normal(Cmax), normal(Ci)) <  θTh
         Pt_result.add(Ci) ;
         delete Ci;
      endif
   endfor
   add Pt_result to Ps;
endwhile
```

Figure 3-3 Coplanarity detection algorithm.

```
Test coplanarity of  planar segments
Inputs:
Planar segments in parallel set  Pi = {C1,C2,..., Cm}
disance threshold: dTh
Initialize:
Sorted Planes by the number of points   P_sorted = Ø
Planar segments list Pt = Ø
Algorithm:
P_sorted = sort(Pi);
While(P_sorted≠ Ø) do
   Cmax = P_sorted.begin();
   Pti.add( Cmax ) ;
   for each Cj=P_sorted{j};
    if minDistance(Cmax, Cj) <  dTh
      combine Cmax and Cj as Cmix;
      C = {C'1,..., C'k} = RANSAC(Cmix);
      Cmax1 = max{C};
      if number(Cmax1) > number(Cmax )
         Pti.add( Cj) ;
         delete Cj  from P_sorte
     C= combine(Pti);
     Pt.add(C);
endwhile
```

Step 3.3: Following the two previous steps, there may still be some coplanar segments that can be combined as one segment, but they are not close enough to be merged as one segment with non-uniform density. The clustering algorithm is employed to detect whether they should be merged. A distance threshold d_{ps} is chosen for clustering coplanar planar segments. The value of the threshold depends on the average distance between points.

Step 3.4: The final step is to detect points belonging to planar segments from residual points left after the previous steps. Based on the distance between points and planes, the points near the identified planar segments will be merged into these segments. This distance is defined using the knowledge base that describes the nature of the surface with its attributes, such as its smoothness. Finally, all the points belonging to planar segments are extracted from the point clouds.

Step 3.5: Steps 3.1 to 3.4 are repeated for each node containing building objects.

The algorithm allows for planar segments detection and extraction from point clouds containing man-made objects. The components of man-made objects are extracted and represented by geometric primitives with corresponding parameters. For other types of objects represented by geometric primitives such as cylinders, similar methods can be developed and applied following the above geometric reasoning framework. For primitives such as spheres and cones, new constraints can be used to merge segments. Based on the information on normal vectors and the distance between two segments, we can decide whether two segments should be merged into one segment or not.

3.6 Experiments and Results

To demonstrate the quality and efficiency of the proposed method, an experimental dataset from the Laval University campus is used. The LiDAR point cloud was observed by a Terrapoint Titan mobile LiDAR system. The LAS file includes information on the georeferenced coordinates, intensity, classification (ground and non-ground), time, number of returns, scan direction flag, scan angle rank, user data and point source ID. The average point spacing in the point cloud is 0.089m. The point density is approximately 130 points/m^2. A higher density of points is observed on the roads. Due to occlusions, scan angle, and objects properties, the point density is non-uniform and objects are incomplete in some parts of the point cloud. In the LAS files, the outlier points are cleaned, and moving objects and noisy points are removed from the raw dataset.

3.6.1 Classify Surface Type

For classifying the surface type, C-SVM classification with RBF kernel is used to classify the model from points of surfaces. The manually selected training dataset includes smooth and unsmooth surfaces from buildings and ground. The LIBSVM (Hsu, 2010) (Chang, 2011) library is used to train the classification model and to predict surface types. After the parameter selection, the C-SVC (C-Support Vector Classification) type, the RBF kernel function, the cost parameters c of C-SVC and γ in the kernel function are chosen using the tools provided in LIBSVM.

3.6.2 Segmentation based on Geometric Reasoning for Buildings

3.6.2.1 Case Study for Buildings with Smooth Surfaces

For a given cluster recognized as a building, the segmentation based on geometric shapes can detect the main components of buildings. In this step, according to the predefined constraints for the segmentation of smooth surfaces, for the building shown in Figure 3-4(A), the results of the region growing segmentation is shown in Figure 3-4(B). We define the minimum threshold θ_{th} 5 degrees to end the region-growing algorithm. After the region growing segmentation, potential planar segments are produced. Then, the RANSAC algorithm is used to detect planar segments using the constraint for smooth surfaces d_{ransac}

($d_{ransac} = 0.1$), as shown in Figure 3-4(C). After using our proposed algorithms to decrease over-segmentation and under-segmentation using the constraints d_p and d_{ps}, the final building components are segmented as shown in Figure 3-4(D).

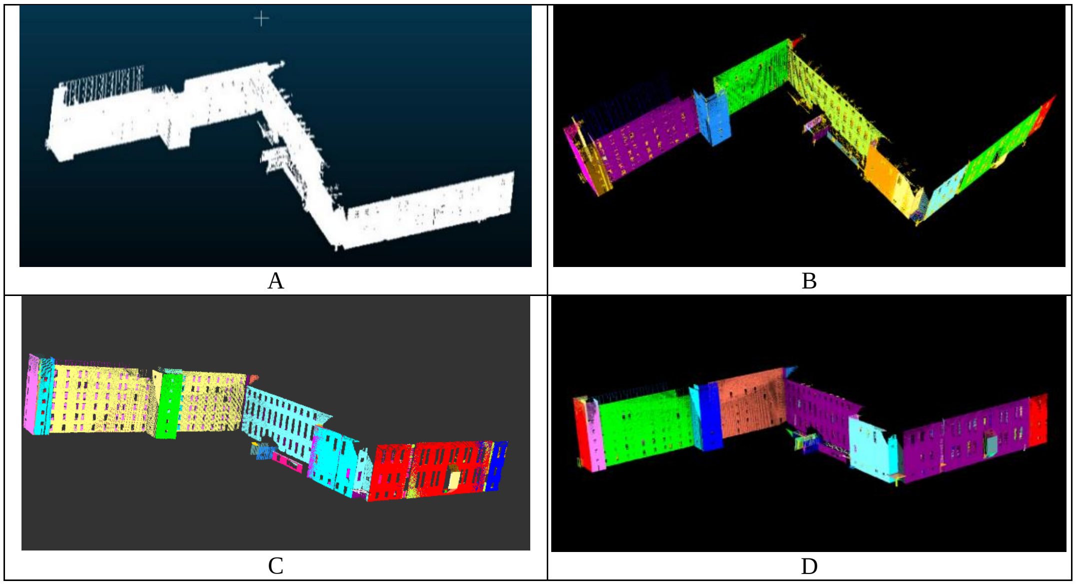


Figure 3-4 A. Unsegmented point cloud; B. Region growing segmentation results; C. RANSAC plane detection results; D. Final segmentation results of our proposed segmentation algorithm.

In order to analyze the parameter sensitivity of our proposed method, we have conducted more experimentations with a new set of parameters for segmenting the dataset used in Figure 3-4. The threshold θ_{th} for ending the region growing segmentation is changed to 8, and the distance threshold d_{ransac} for plane detection in RANSAC is 0.3 metres. To compare the original building structure and the segmentation results, the image of the building is extracted from Google Earth as shown in Figure 3-5(A). The results of the region growing segmentation using the new threshold are shown in Figure 3-5(B). The final segmentation results of the planar components of this building are shown in Figure 3-5(C). The comparison between the segmentation results in Figure 3-4(D) and Figure 3-5(C) shows that the main planar components are all segmented correctly. After the test of changing the parameters, the results showed that our proposed shape-based segmentation is not sensitive to the smoothness threshold used in the region growing algorithm and to the distance threshold used to detect planes.

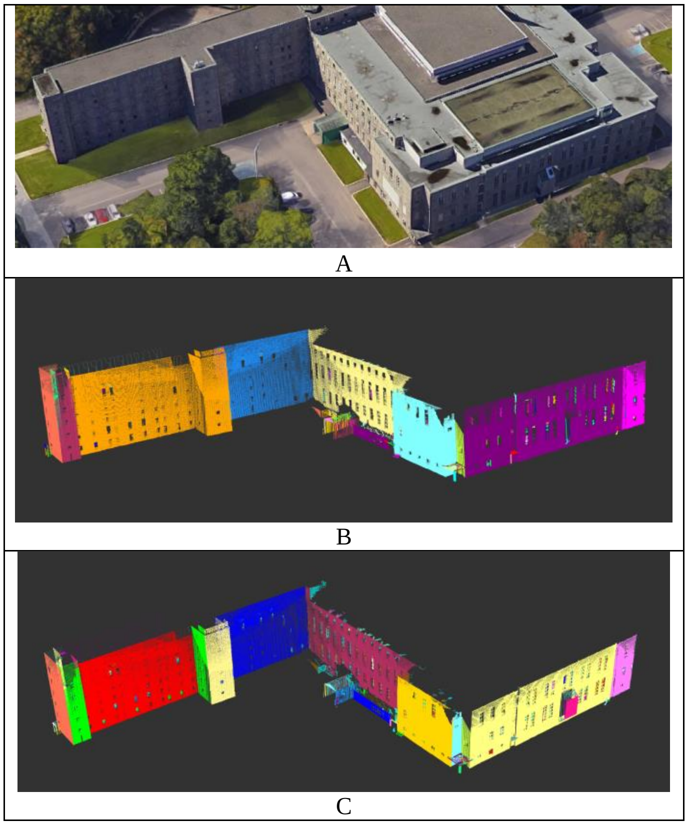
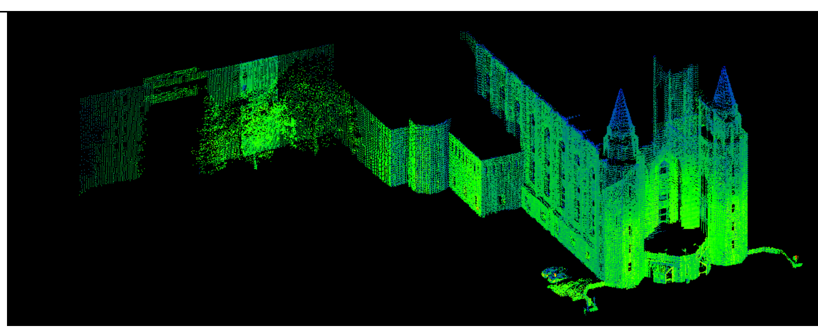


Figure 3-5 Segmentation results. (A). Image from Google Earth to show the structure of the building; (B). Region growing segmented results using new parameters; (C). Final segmentation results of our proposed segmentation algorithm using new parameters.

The proposed segmentation algorithm has been tested on other parts of the building (Figure 3-6). Considering the small planes in the structure of this building, the minimum size for the detection of building components is 0.3 m^2. The segmentation results are shown in Figure 3-6(C) and D). The detailed segmentation results of some detailed parts of the building are shown in Figure 3-6(E). After the segmentation, there are 246 planar segments detected in the point cloud.



A

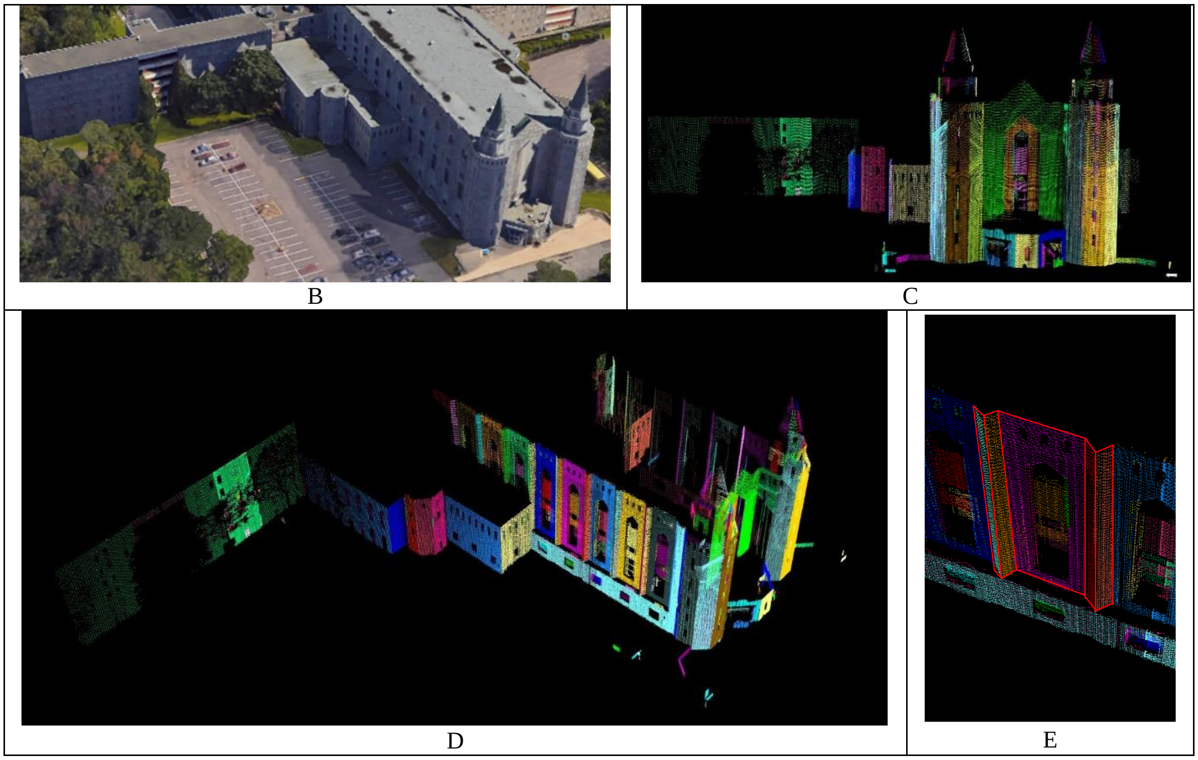


Figure 3-6 Segmentation results. (A). The input point cloud dataset; (B). Image from Google Earth showing the structure of the building; (C). Segmentation results of some parts of the building using our proposed methods; (D). Segmentation results of the building shown from another perspective; (E). Local information of a part of the surface in (D).

3.6.2.2 Case Study for Buildings with Unsmooth Surfaces

When clustering objects, there may be some cases where it is difficult to separate points belonging to different objects, for example, when one object occludes another (occlusion case). In this case, a part of the occluded object may be absent in the point cloud. As we can see in Figure 3-7(A) and (C), a part of the building is occluded by trees, and they are very close in the point cloud. We can also see that the wall surface is not smooth due to the outer rectangle curtain wall in Figure 3-7 (B). After the region growing segmentation using the calculated smoothness threshold (Figure 3-7 (D)). The θ_{th} for ending the segmentation of unsmooth surfaces was defined as 15 degrees. Then, RANSAC segmentation was applied to segment the results of the region growing algorithm. Again, from the planar segments acquired by RANSAC, we can see that there are several over-segmented planar segments (Figure 3-7 (E)). To decrease the over-segmentation, the main structures of the building have been segmented as shown in Figure 3-7 (F) after applying our proposed algorithms. The experiment results reveal that a point cloud with non-uniform density and occluded parts can still be segmented and the main planar structures of the building can be obtained using our proposed method. As a result of our method, an occluded wall is segmented into two planar segments as shown in blue and orange in Figure 3-7 (F). Also, compared to the results of typical region growing and RANSAC algorithms in Figure 3-7 (D) and (E), the over-segmented cases have decreased a lot after using our proposed solution (Figure 3-7 (F)). In conclusion, the proposed solution is robust to segment man-made objects with complex structures and mixtures of man-made objects and other objects in a cluster.

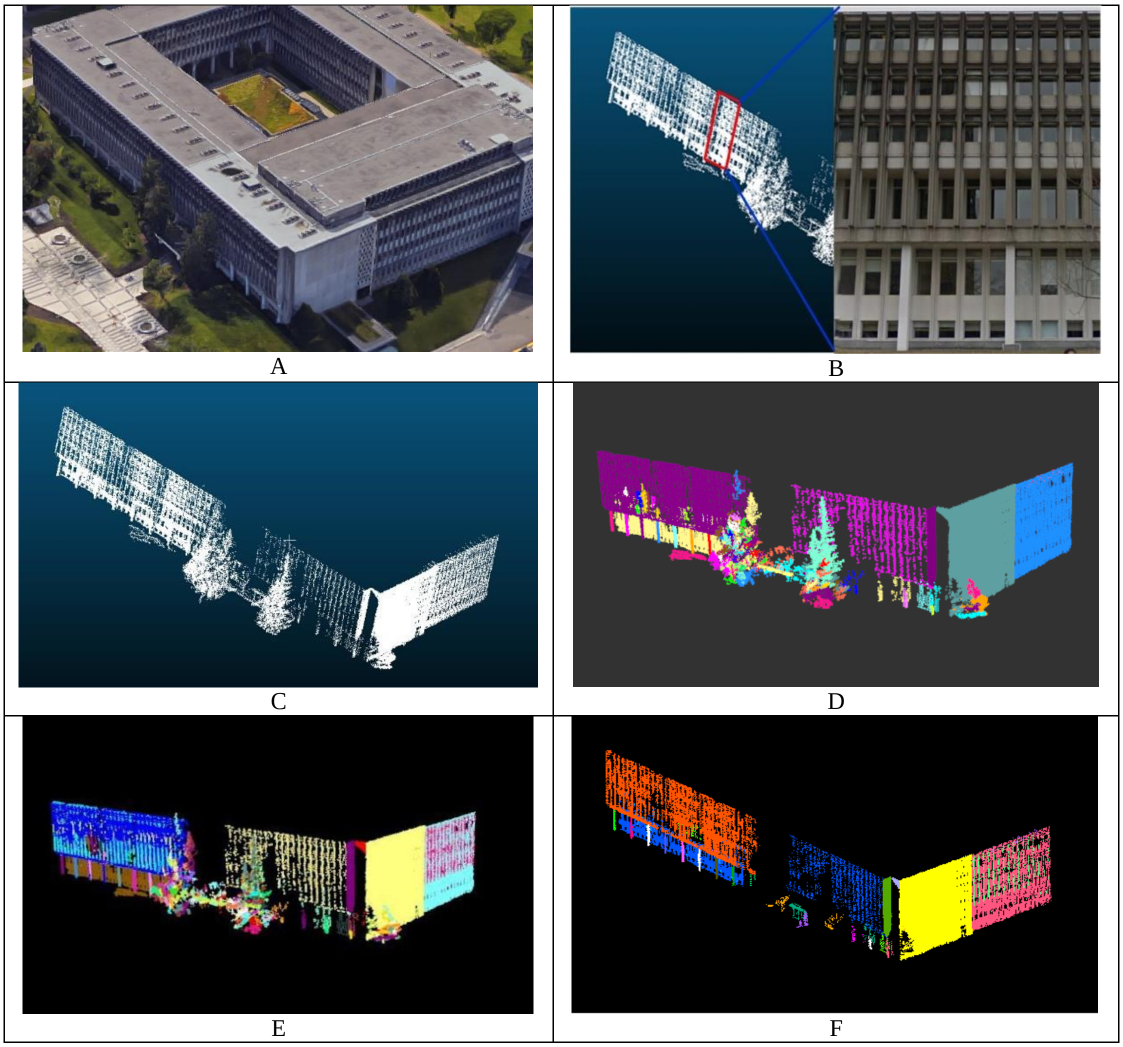


Figure 3-7 Segmentation results. (A). Image from Google Earth showing the structure of the studied building; (B). Details after zooming in; (C). Point cloud consisting of building and trees; (D). Region growing segmentation results; (E). RANSAC planar segmentation results; (F). Final segmentation results of our proposed segmentation algorithms.

3.7 Discussion

The results obtained from our experiments show the effectiveness of the proposed approach. As we can see from the segmentation results in the previous section, most over-segmentation problems of man-made objects with complex structures can be avoided effectively, especially for those objects with smooth surfaces. Even if our proposed algorithms are not perfect to segment man-made objects with unsmooth surfaces and for non-uniform point density, over-segmented components can be eliminated to a great extent. In our experiments, the planar segments with uniform point density were all segmented correctly. The missing points due to the occlusion of part of the building's wall have led to the over-segmentation of the wall (in Figure 3-7). For evaluating the accuracy of the segmentation results, we calculated the recall, precision and F-score using the rules presented in (Li, 2012b; Nurunnabi, 2015). The recall (r) represents the surface segmentation rate. The precision (p) means the correctness of the segmented surface. The F-score (F) indicates the overall accuracy. They are defined as:

$$r = \frac{PS}{PS + US} \times 100 \quad \textbf{(Eq 3-4)}$$

$$p = \frac{PS}{PS + OS} \times 100 \quad \textbf{(Eq 3-5)}$$

$$F = 2 \times \frac{r * p}{r + p} \quad \textbf{(Eq 3-6)}$$

where PS=Proper Segment, US=Under Segment, OS=Over segment.

As shown in Table 3-2, in Figure 3-4, the 36 planar components are segmented correctly. But a cylindrical pillar is over-segmented as two planar segments because the density of point clouds is not high enough to distinguish its surface type. For the segmentation results in Figure 3-6, we segmented 246 planar segments. But there are 8 missing planar segments because the area of these planes is small and the points are sparse on top of buildings scanned by mobile LiDAR scanners due to the scanning angle. There are 17 planar components in Figure 3-7, including walls and planar pillars. A wall is over-segmented due to sparse points caused by the occlusion. Therefore, incomplete and sparse point clouds or improper segmentation models used for components with non-planar geometric shapes may cause over-segmentation.

Table 3-2 Analysis of the experiments results (DS=Detected Segments, MS=Missing Segments)

Dataset	DS	PS	US	OS	MS	r(%)	p(%)	F(%)
In Figure 3-4	38	36	0	1	0	100	97.29	98.63
In Figure 3-6	246	241	2	5	8	99.17	97.96	98.56
In Figure 3-7	17	15	0	1	0	100	93.75	96.77

3.8 Conclusion and Future Work

In this paper, we have proposed a method of CAD-like segmentation of buildings with complex structures. Based on the results of pointwise segmentation, the points belonging to the building class are separated. The surface type is classified by our proposed features. Then, surface smoothness is used as a crucial property to define appropriate thresholds for the segmentation of building components with different levels of smoothness. Based on the information surface type, we proposed a solution to decrease over-segmentation cases. The results demonstrate that the proposed solution is not very sensitive to the parameters value selection and is very flexible and efficient for the segmentation of buildings with complex structures in an urban scene. For evaluating our proposed solution, the experimental results were analyzed using the recall, precision, and F-score. We can conclude that more than 99% of building components can be segmented from an urban scene according to the recall value in the analysis of the experiment results.

The proposed segmentation method for objects in urban scenes can be extended to other man-made objects. As future work, we plan to integrate other data sources into the segmentation process. Additionally, we need more investigation to improve the robustness of the segmentation framework for the segmentation of different types of objects, such as curb, pole, and road in a complex urban scene.

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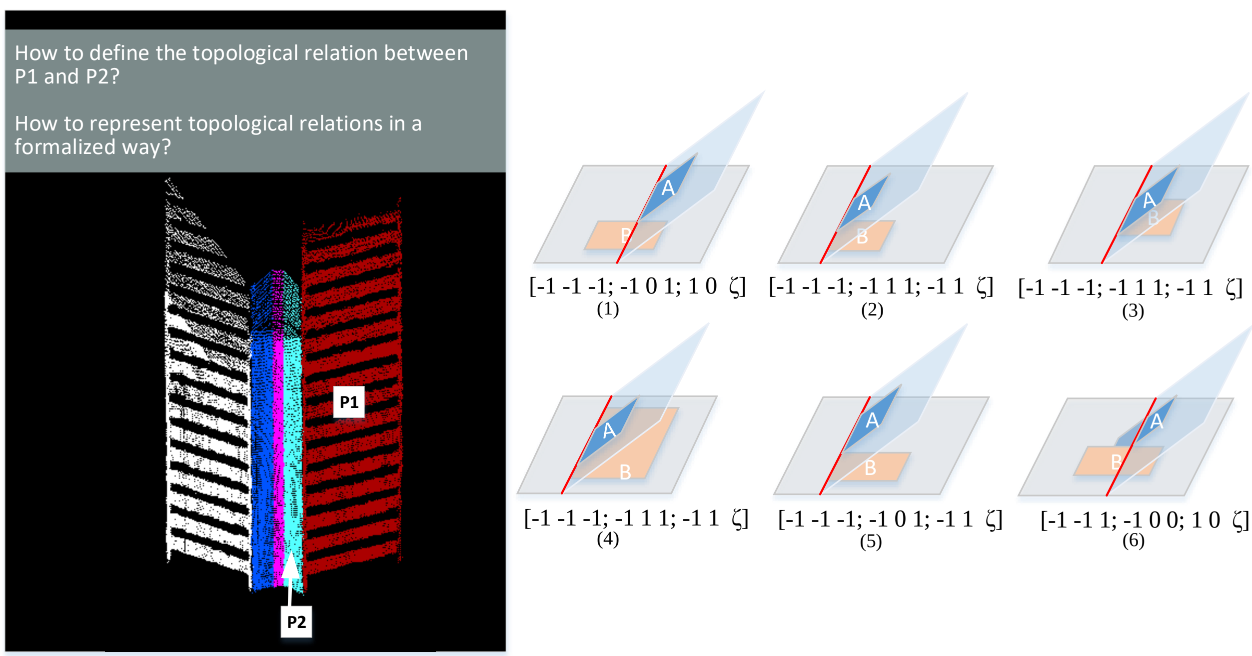
Introduction of Article

Extension of RCC Topological Relations for 3D Complex Objects Components Extracted From 3D LIDAR Point Clouds

Topological relations are fundamental to spatial reasoning, spatial analysis and spatial querying in practical application. The definitions of topological relations between object components are necessary to assemble components into a whole object. More importantly, the formalized representation of topological relations makes it possible to be used in spatial reasoning and knowledge reasoning based on topologies. In chapter 4, we will solve the problems of the limitations of the existed models for representing topologies among object components in B-Rep 3D models. The proposed models for formalizing topological relations among object components aim to distinguish the possible topological relations between components in urban scenes.



(A) Segmentation results

(B) Models for identifying and formalizing topological relations between components

Figure VI the expected work in the step of identifying topological relations among object components

In chapter 4, first we introduce the models for representing topologies in 2D and 3D space. We noticed that the existing models cannot represent the topological relations among object components for constructing B-Rep 3D models. Thus, we propose an extension of RCC topological relations for complex object components. A component is abstracted as a planar region that is defined as a planar surface area with a non-empty, connected interior in R^3. The topological relations between planar regions are divided into three parts: the topological relations between two planar regions and the intersection line constructed by two planes contain planar regions, and the topological relations between the intersected common parts of planar regions and the intersection line. The extended 9-Intersection Model is defined to record the topological relations in a formalized way, which is informative to distinguish detailed topological relation between object components. The experiments are conducted to show its capabilities of representing topological relations among building components segmented from point clouds of urban scene.

CHAPTER 4 Extension of RCC Topological Relations for 3D Complex Objects Components Extracted From 3D LIDAR Point Clouds

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4.1 Résumé

Les relations topologiques sont fondamentales pour la description qualitative, l'interrogation et l'analyse d'une scène 3D. Bien que les relations topologiques pour les objets 2D aient été largement étudiées et implémentées dans les applications SIG, leur extension directe à la 3D est très difficile et ne peuvent pas être appliquées directement pour représenter des relations entre des composants d'objets 3D complexes représentés par des modèles 3D B-Rep en format. Nous présentons ici un modèle RCC (Region Connection Calculus) étendu permettant d'exprimer et de formaliser des relations topologiques entre des régions planaires afin de créer un modèle 3D représenté par le modèle de représentation des limites dans R^3 .Nous avons proposé un nouveau modèle à 9 intersections élargies pour représenter les relations de base entre les composants d'un objet complexe, notamment les objets disjoints, se rencontrent et se croisent. Le dernier élément de la matrice 3 * 3 enregistre les détails de la connexion à travers les parties communes de deux régions et la ligne d'intersection de deux plans. De plus, ce modèle peut traiter le cas de régions planaires avec des trous. Enfin, les informations géométriques sont transformées en une liste de chaînes constituées de relations topologiques entre deux régions planaires et d'informations de connexion détaillées. Les expériences montrent que l'approche proposée aide à identifier automatiquement les relations topologiques des segments plans du nuage de points.

4.2 Abstract

Topological relations are fundamental for qualitative description, querying and analysis of a 3D scene. Although topological relations for 2D objects have been extensively studied and implemented in GIS applications, their direct extension to 3D is very challenging and they cannot be directly applied to represent relations between components of complex 3D objects represented by 3D B-Rep models in R^3 . Herein we

present an extended Region Connection Calculus (RCC) model to express and formalize topological relations between planar regions for creating 3D model represented by Boundary Representation model in R^3. We proposed a new dimension extended 9-Intersection model to represent the basic relations between components of a complex object, including disjoint, meet and intersect. The last element in 3*3 matrix records the details of connection through the common parts of two regions and the intersecting line of two planes. Additionally, this model can deal with the case of planar regions with holes. Finally, the geometric information is transformed into a list of strings consisting of topological relations between two planar regions and detailed connection information. The experiments show that the proposed approach helps to identify topological relations of planar segments of a point cloud automatically.

Keywords: Topological relations, planar regions, components, automatic 3D modelling, point cloud

4.3 Introduction

Spatial relations include topological, metric and directional relations and together with semantic information are used for describing a scene qualitatively (Mark, 1994). Topological relations between geographical objects are necessary for spatial analysis in GIS. These relations can be queried and analysed independently from geographic coordinate system definition and the specific location of objects. Topological relations describe relative spatial relations with respect to reference objects. Hence topological relations are invariant and do not change with topological transformations, such as translation, scaling, and rotation (Egenhofer, 1990b).

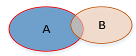
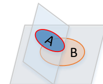
In general, topological relations between spatial objects are derived from Region Connection Calculus (RCC-8) (Egenhofer, 1989; Egenhofer, 1991b) in R^2. Existing RCC have been further applied to Qualitative Spatial Reasoning (QSR) in the field of GIS, robotics, medicine and engineering problems for the reasoning of the topological relationships in R^2 (Cohn, 2008). Here, a region is defined as a 2-cell with a non-empty, connected interior (Egenhofer, 1990a). Additionally, the 4-Intersection Model (4IM) (Egenhofer, 1991b), 9-Intersection Model(9IM) (Clementini, 1993) and Dimensionally Extended models (DE) (Clementini, 1993) are widely adopted and implemented for describing topological relations for spatial analysis. Topological relations between spatial objects can be described based on relations defined for 2D regions in RCC model. Basic relations between two regions include disjoint, meet, overlap, contain, cover, coveredBy, containedBy and equal (Egenhofer, 1990b; Randell, 1992).

The definitions of topological relations between spatial objects in R^3 are closely related to 3D objects models. A 3D spatial object can be modelled as a solid geometry or represented by its boundaries. Thus, topological relations between spatial objects in R^3 can be divided into two aspects: topological relations between 3D complex objects and topological relations between components of a complex object. For 3D objects represented by boundary representation (B-Rep), there exists the concepts of the interior, boundary, and exterior of objects. The topological relations between 3D spatial objects represented by B-Rep can be directly extended to define eight basic topological relations in R^3 (Zlatanova, 2004). However, in this paper, we concentrate on topological relations among object components in a single 3D spatial object represented by B-Rep rather than relations between 3D complex objects. However, the topological relations between objects components are not the same as relations between complex objects themselves. Additionally, the boundaries of 2D objects can be extracted and represented by polygons in R^2, similarly, the boundaries of 3D objects can be modelled as facets. Here, facets are composed of small planar surfaces such as triangles for representing surfaces. Referring to the definition of the region in R^2, a planar region in R^3 is defined as a planar surface area with a non-empty, connected interior in R^3. A planar region is described by its boundaries and the parameter of the plane equation in which planar regions are located. Therefore, the topological relations between components of a complex object represented by B-Rep can be modelled as the relations between planar regions in R^3 .

For creating 3D B-Rep models from point clouds, we need the topological relations between points, the relations between components of complex objects and objects themselves in three different levels (Pigot, 1991). For representing objects with complex structure, such as buildings, using B-Rep models, topological relations between components provide the connection of components to form a whole 3D model with interior space. Unlike the definitions of 3D simple geometric primitives, such as the sphere, cube, and cylinder (Leopold, 2015), a planar region in R^3 does not have a volume. In 3D B-Rep models, a planar region can represent a part of a 3D complex object boundary. The topological relations between planar regions connect all boundaries parts together to represent a 3D object. Thus, topological relations between planar regions play an important role in creating 3D B-Rep models from a point cloud. More importantly, the definition of the boundary of a planar region in R^3 (for example a part of a wall represented as a rectangle in R^3) depends on plane equation that contains planar regions and the definition of its boundary is needed to determine the topological relations among planar regions.

The existing topological models have limitations to meet the requirements of building topological relations of object components to form a whole 3D B-Rep model. For example, in Table 4-1, the overlap relation between region A and B in R^2 can be represented by 4IM as a matrix [1 1; 1 1]. But if RCC-8 is directly applied to determine topological relations, we will get [0 0; 1 0] in R^3. It cannot be defined as overlap. It is needed to extend these relations to describe the topological relation of two planar regions in R^3

Table 4-1 The differences of topological relations between two regions in R^2 and R^3

Space type	Figure example	Representation of 4IM
R^2		$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$
R^3		$\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}$

Some studies propose RCC extension in response to those limits. For example, topological relations extended from RCC model are defined and distinguished as non-occlusion, partial occlusion and complete occlusion relations in the projected planes in a specific perspective in RCC-3D (Albath, 2010b) and VRCC-3D+ (Albath, 2010b; Sabharwal, 2011). However, they did not involve the topological relations between objects components. Therefore, a formalized representation and discrimination method for the topological relations between 3D planar regions are an indispensable part of 3D modelling and spatial analysis.

In this paper, we are concerned with the determination of the topological relations between planar regions in 3D space generated from point clouds (ex. LiDAR point clouds). We present an overview of generalized topological models for describing relations between planar regions in R^3 and then based on the definitions of basic eight topological relations, a new extended topological model from RCC is proposed to define topological relations among planar regions. In addition, the validation of the extended RCC model is conducted to identify topological relations between buildings components consisting of planar regions extracted from point clouds.

The reminder of this paper is organized as follows. Section 2 briefly discusses 3D model representation methods that are suitable for 3D modelling from point clouds, and their advantages and limitations. In addition, the RCC, 4IM, 9IM and DE9IM in R^2, and other studies related to topological relations in R^3 are discussed. In section 3, topological relations for planar regions are defined and formally represented. Moreover, the steps for deciding topological relations are presented. Section 4 validates the proposed topological models for planar regions on a point cloud dataset. The processes of deciding relations among planar regions segmented from point clouds are given as well. Section 5 outlines conclusions and future work.

4.4 Related Work

4.4.1 3D Objects Representation Methods

Boundary Representation, also called as B-Rep, describe 3D objects boundaries composed of vertices, edges and faces (Jarroush, 2004). In a B-Rep model, geometric information is derived from the coordinate of vertices. The geometric information describes its shapes and its boundaries constrained by vertices, edges, and faces. The topology between different components describes the connectivity relationships among basic primitives of boundaries. For example, a part of point cloud observed to model a planar wall provides basic geometric information through the coordinate points. The shape of a wall is determined by the parameters of a plane equation and its boundary. The connection between several walls are described by topological relations. For objects with complex structure, B-Rep represents objects based on their fundamental geometric primitives to create a complete model with the help of topology. Therefore, B-Rep is capable of creating 3D models of complex objects, and it can describe their surface boundaries accurately. However, B-Rep model is not very efficient for the representations of complex solid objects because it needs a large volume of data to represent them (Koussa, 2009).

Constructive Solid Geometry (CSG) model creates a complex object using Boolean operations (including intersection, union, and difference) among basic primitives, such as cubes, cylinders, cones, and spheres (Foley, 1996). However, it has limitations to create complex objects with irregularly curved surfaces. More importantly, CSG does not provide a unique representation, which will yield different results (Foley, 1996). In conclusion, for automatic 3D modelling of point clouds, the simple operations between primitives in CSG are not enough to represent complex structures of objects and irregular shapes of objects.

Another approach for modelling 3D objects is the "Parametric approach" (Koussa, 2009). In this approach, an object is modelled by its primitive components. These primitive geometric objects are defined by a set of parameters. Geometric information of these objects consists of length, height, width, angle and diameter. These geometric parameters and the relationships among components are allowed to be defined by users. Thus, it is flexible to represent geometric models, and some semantic information can be attached. In general, these kinds of information are manually set by users (Koussa, 2009). However, if the geometric parameter can be acquired from point clouds, this method is helpful to represent planar regions. Therefore, this method can be employed in automatic 3D modelling if geometric parameters are obtained from point cloud automatically. For those nonplanar primitives (such as a cylinder, cone, and torus), parametric approach briefly describes geometric models by several parameters as well. However, the topological relations between planar regions are the cores of 3D topologies because complex shapes can be decomposed into simple planar primitives. Also, for the purpose of determining topological relationships of planar regions from point clouds, the accurate boundary information still requires geometric parameters of planar regions.

For automatic 3D modelling from point clouds, B-Rep is more adaptable because point clouds record the outer surface information of objects in points. As for various kinds of objects, B-Rep has the capability of describing complex shapes and spatial structures of objects due to the topological relationships built from vertices, edges, and faces. Additionally, B-Rep can represent 3D objects with complex structure through the topological relationships among simple geometric primitives. Especially for complex irregular shapes, B-Rep can use triangulation for surface representation where topologies can be defined the relations between simple triangular faces.

In conclusion, considering the advantages and limitations of the presented models, we propose a hybrid approach that combines parametric approach and B-Rep models to define topological relations between components of a complex object in a 3D space.

4.4.2 Models for Topological Relations

4.4.2.1 **Calculus-based Spatial Logic Model:**

In 2D space, Region Connection Calculus (RCC) is one of the fundamental methods for the definition of topological relationships. In this model, topological relationships are grouped into six categories including relations between point-point, point-line, point-region, line-line, line-region, region-region. Among these relations, region-region relations are the most commonly used to express topological relations between different primitives (Deng, 2007). The existing eight topological relations (RCC-8) are (Randell, 1992): disconnected (DC), partial overlap (PO), equal (EQ), externally connected (EC), tangential proper part (TPP), non-tangential proper part (NTPP) and their inverse relations are TPPi and NTPPi respectively. Additionally, RCC describes the logic representations of spatial relations between regions (Randell, 1992). Also, these eight relations can also be converted from one relation to another to describe topological relations in a dynamic scene.

4.4.2.2 **Intersection Model:**

In "4-Intersection" Model (4IM) (Egenhofer, 1989; Egenhofer, 1991b), eight topological relationships between two regions are defined. They are disjoint, meet, overlap, contain, cover, coveredBy, containedBy and equal. These relations correspond to RCC-8 relations: DC, EC, PO, NTPP, TPP, TPPi, NTPPi, EQ, respectively. They are obtained by the intersection between boundaries and interiors of two primitive geometries (ex. region). A matrix $T(A,B)$ consists of the intersection of boundaries and interiors of region A and B. The intersection values are distinguished only by "empty" and "non-empty" value. 0 and 1 represent the empty and non-empty, respectively.

$$T(A,B) = \begin{bmatrix} A^{\circ} \cap B^{\circ} & A^{\circ} \cap \partial B \\ \partial A \cap B^{\circ} & \partial A \cap \partial B \end{bmatrix} \quad \textbf{(Eq 4-1)}$$

Where A° = the interior of region A

∂A = the boundary of region A

B° = the interior of region B

∂B = the boundary of region B

The eight relations are shown as follows: disjoint(A,B) = [0 0;0 0], meet(A,B)= [0 0;0 1], overlap(A,B) = [1 1;1 1], cover(A,B) = [1 1;0 1], contain(A,B)= [1 1; 0 1], coveredBy(A,B)= [1 0;1 1], containedBy = [1 0;1 0], equal(A,B) =[1 0; 0 1].

In "9-Intersection" Model (9IM) (Egenhofer, 1993; Egenhofer, 1990a), for definition of topological relations, in addition to interiors and boundaries of the regions, the exteriors are also considered. The "9-Intersection" model easily extends the "4-Intersection" to nine elements using a 3*3 matrix.

$$T(A,B) = \begin{bmatrix} A^{\circ} \cap B^{\circ} & A^{\circ} \cap \partial B & A^{\circ} \cap \mathrm{B}^{e} \\ \partial A \cap B^{\circ} & \partial A \cap \partial B & \partial A \cap \mathrm{B}^{e} \\ A^{e} \cap B^{\circ} & A^{e} \cap \partial B & A^{e} \cap \mathrm{B}^{e} \end{bmatrix} \quad \textbf{(Eq 4-2)}$$

Where A° = the interior of the region A

∂A = the boundary of the region A

A^{e} = the exteriors of region A

B° = the interior of region B

∂B = the boundary of region B

B^{e} = the exteriors of region B

Even though the exterior of objects adds more expressiveness to the topological relations, no more relations between region-region are distinguished in "9-Intersection" model (Chen, 2001). The topological relations of "9-Intersection" are defined for eight relations as follows (Clementini, 1994): disjoint(A,B) = [0 δ δ ;

δ 0 δ ; δ δ δ], meet(A,B)= [0 δ δ ; δ 1 δ ; δ δ δ], overlap(A,B) = [δ 1 δ ; 1 δ δ ; δ δ δ], cover(A,B) = [δ 1 δ ; 0 1 δ ; δ δ δ], contain(A,B)= [δ 1 δ ; δ 0 δ ; δ δ δ], coveredBy(A,B)= [δ 0 δ ; 1 1 δ ; δ δ δ], containedBy = [δ δ δ ; 1 0 δ ; δ δ δ], equal(A,B) =[δ δ δ ; 0 δ 0; δ δ δ]. Here 0 and 1 represent the empty and non-empty, respectively. Each δ indicates a value that we don't care. The 4IM and 9IM are easy to be implemented in practical applications. But they have limitations to determine the more expressive relations between parts of a 3D complex object.

4.4.2.3 The Dimensionally Extended Model:

For the purpose of describing detailed topological relations, the dimensionally extended method was presented by Clementini et al. (Clementini, 1993). In this method, values -1,0,1 and 2 are used to qualify the intersection between two regions. If there is no intersection, -1 is used to indicate null set. 0 implies that intersection result contains, at least, one point and no lines or areas. Similarly, 1 indicates that the intersection contains, at least, a line and no area. Finally, 2 indicates that the intersection contains at least an area. Based on these definitions, the dimension of the intersection is taken into account in the topological relations. The five topological relations, including touch, in, cross, overlap and disjoint, are defined and analysed. These relations are used to define the topological relations among point, line, and area. These relations are proved to be mutually exclusive because they meet the criteria of Jointly Exhaustive and Pairwise Disjoint (JEPD). A decision tree is provided to discriminate topological relationships with the aid of dimension definition. Additionally, Multi-level topological relations are presented based on 4-Intersection model. The intersection and difference model replaces the original intersection model for reducing the computation complexity of spatial operation between regions. Moreover, the definitions of topological complexity and topological distance are introduced to classify the eight relations. Five topological invariants are applied to decide further the detailed level of topological relations hierarchically. This method can determine more detailed topological relations between two regions based on topological invariants (Deng, 2007).

The Dimensionally Extended 9-Intersection Model (DE-9IM) (Strobl, 2008) is a full descriptive assertion about two spatial objects in R^2. The "9-Intersection" model belongs to binary classification. The values of elements in "9-Intersection" model can be either empty or non-empty. However, the corresponding elements in DE-9IM become the dimension operation of those elements in the "9-Intersection" model.

$$T(A,B) = \begin{bmatrix} \dim(A^{\circ} \cap B^{\circ}) & \dim(A^{\circ} \cap \partial B) & \dim(A^{\circ} \cap B^{e}) \\ \dim(\partial A \cap B^{\circ}) & \dim(\partial A \cap \partial B) & \dim(\partial A \cap B^{e}) \\ \dim(A^{e} \cap B^{\circ}) & \dim(A^{e} \cap \partial B) & \dim(A^{e} \cap B^{e}) \end{bmatrix} \qquad \textbf{(Eq 4-3)}$$

Where A° = the interior of the region A

∂A = the boundary of the region A

A^{e} = the exteriors of region A

B° = the interior of region B

∂B = the boundary of region B

B^{e} = the exteriors of region B

dim() = dimension operator

Here $dim(s)=max\{dim(s_1), dim(s_2), \ldots, dim(s_n)\}$, and s_i is the spatial set of intersection of the interior, boundary and exterior of region A and B. So the possible dimension values are in the set of $\{-1, 0, 1, 2\}$. -1 means empty set, 0 for points, 1 for lines and 2 for areas. But for querying of topological relations, the 3*3 matrix are formatted as a string code. The DE-9IM code is an accepted standardized format in the OGC standards. The DE-9IM have been implemented in PostGIS for data analysis (Boundless, 2014). More importantly, it can transform geometric information into semantic descriptions of topological relations.

4.4.2.4 **RCC in 3D Space:**

Among all the 512 possible relations in 9IM, eight relations are easily recognizable in R^2. Similarly, eight relations can apply to 3D objects in R^3 (Zlatanova, 2004). Because RCC may define regions as continuous space representation, Generalized 2D Region Connection Calculus (GRCC) (Li, 2004) extends RCC for both infinite real space and discrete space for the purpose of analysing topological relations between regions in discrete space, such as regions extract from images and point clouds. Thus, RCC-3D (Albath, 2010b) extends the spatial reasoning in R^3 based on GRCC, and it introduces new relations by adding the relations of objects projected in principle planes perpendicularly in R^3 (ex. objects projected to planes formed by xy-axes, yz-axes and zx-axes). The combination of five predicates and a converse predicate can uniquely identify 13 RCC-3D relations between a pair of 3D objects or multiple objects in the case of no a priori knowledge about the underlying relations(Albath, 2010a). VRCC-3D+ (Sabharwal, 2011) used RCC-3D and depth parameter to distinguish non-occlusion, partial occlusion and complete occlusion relations in R^3, which relies on the viewpoints and the projection planes. Essentially, these methods transform the topological relations into 2D plane to determine relations in R^3. Meanwhile, the definitions of topological relations models are derived from RCC-8 in R^2.however, these models cannot be applied to determine topological relations among object components in the B-Rep 3D models.

In conclusion, RCC-8 is the used to define topological relations in R^2. It is also used for analysing the topological relations in R^3. For the topological relations between components of objects represented by the B-Rep model, the extended DE-9IM is more effective. This model helps to describe the topological relations between components of a complex object by integrating information from parametric approach.

4.5 Topological Relationships among 3D Planar Regions forming a complex 3D Object

4.5.1 Definition of Topological Model for Planar Region

For determination of topological relations between planar regions in 3D space, their boundary and interior of planar regions are critical. The geometric representation of a plane in R^3 is formally defined by $\mathrm{Ax} + By + Cz + D = 0$. But this equation defines a plane without any boundary. Thus, we need not only define a planar region by a plane equation, but also we need to determine its boundaries, and its interior.

Topological relations between planar regions in R^3 are firstly dependent on the spatial relations between two planes (SRp) in which planar regions locate. Then topological relations of planar regions (TRr) can be determined based on SRp. The set of SRp is $\{parallel,\ coplanar,\ intersecting\}$. TRr still are defined based on the eight topological relations defined in 4IM. If the value of SRp is parallel, two planar regions must be disjoint. If the value of SRp is coplanar, then the relations between 3D planar regions become relations between regions in 2D space. The intersecting case of SRp results in more detailed topological relations between planar regions in R^3.

When SRp is the intersecting case, according to the definitions of the calculus-based model, “Disjoint” is the case that there is no common part between two planar regions. “Meet” is decided when there is and only is a common part of the boundaries of two planar regions in the intersection line. Except disjoint and meet, intersect relation covers all other remaining relations. The main topological relations for the intersecting case of SRp can be classified as disjoint, meet and intersect cases. The topological relations between planar regions can be divided into the relations between intersecting line of two planes and two planar regions because intersecting line is the only possible connection between two planar regions.

Based on the spatial relations of planes, the topological relations of two planar regions are closely related to the relations between intersection line of two planes and each planar region. Therefore, intersection line, the boundaries and interiors of two planar regions are used to define topological relations between planar regions in a 3*3 matrix as in DE-9IM as follows:

$$T_p(A,B) = \begin{bmatrix} \dim(A^\circ \cap B^\circ) & \dim(A^\circ \cap \partial B) & \dim(A^\circ \cap Il_B) \\ \dim(\partial A \cap B^\circ) & \dim(\partial A \cap \partial B) & \dim(\partial A \cap Il_B) \\ \dim(Il_A \cap B^\circ) & \dim(Il_A \cap \partial B) & \dim(Il_A \cap Il_B) \end{bmatrix} \quad \textbf{(Eq 4-4)}$$

Where A° = indicates the interior of the region A

∂A = the boundary of A

B° = the interior of region B

∂B = the boundary of the region B

Il = intersection of two planes containing two planar regions. Here Il_{A} and Il_{B} share the same line equation.

dim() = dimension operator

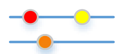
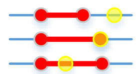
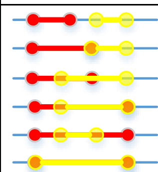
Because the value of $\dim(Il_A \cap Il_B)$ is always 1, it cannot provide more details to describe topological relations. However, the intersection primitives of Il and a planar region could be points or line segments. For providing detailed descriptions of topological relations between these primitives, the $\dim(Il_A \cap Il_B)$ is replaced by ζ. The ζ indicates topological relations of two parts of intersection primitives (points and lines) constituted by the intersecting line and two planar regions individually. Thus, the original matrix is represented as follows:

$$T_p'(A,B) = \begin{bmatrix} \dim(A^\circ \cap B^\circ) & \dim(A^\circ \cap \partial B) & \dim(A^\circ \cap Il_B) \\ \dim(\partial A \cap B^\circ) & \dim(\partial A \cap \partial B) & \dim(\partial A \cap Il_B) \\ \dim(Il_A \cap B^\circ) & \dim(Il_A \cap \partial B) & \zeta \end{bmatrix} \quad \textbf{(Eq 4-5)}$$

Topological relations between intersection primitives lying in the intersection line are comprised of the relations of point-point, point-line, line-line in the same line equation, so it contains disjoint, meet, overlap, covers, contains, coveredBy, containedBy and equal as well (as shown in Table 4-2). Additionally, ζ is represented by a list of string, including the description of topological relations between primitives in intersection line, Il_A^{rl} and it geometric type, Il_B^{rl} and its type, the common part of Il_A^{rl} and Il_B^{rl}, here Il_A^{rl} indicates the common parts of region A and the intersection line, and Il_B^{rl} means the common parts of region

B and the intersection line. Therefore, ζ is designed to discriminate the detailed topological relations on the basis of other eight elements of the matrix.

Table 4-2 Basic topological relations between primitives in the intersection line of two planes (red primitives are the intersections between planar region A and the intersecting line, and yellow parts are the intersections between planar region B and the intersecting line)

Type of relations	Graphical representation
Point-point relations	 disjoint equal
Line segment-point relations	 disjoint meet contain
Line segment-line segment relations	 disjoint meet overlap cover contain equal

As shown in Figure 4-1, for the case of disjoint between line segment and line segment, ζ = [disjoint, < $P_{1A}P_{2A}$, line segment>, < $P_{1B}P_{2B}$, line segment>, $\varnothing$].

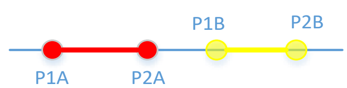


Figure 4-1 Disjoint case between line segments resulted from the intersection of two planar regions and intersecting line of two planes

Similarly, for the case of overlap, ζ = [overlap, < $P_{1A}P_{2A}$, line segment>, < $P_{1B}P_{2B}$, line segment>, < $P_{1B}P_{2A}$, line segment>]. For meet relation we have ζ = [meet, < $P_{1A}P_{2A}$, line segment>, < $P_{1B}P_{2B}$, line segment>, < P_{2A} , point>].

However, for those regions with holes, the ζ is composed of a set of relations that is represented by a list of ζ_i. For example, in Figure 4-2, there is a hole in region B. for this case, ζ = [[overlap, < $P_{1A}P_{2A}$, line segment>, < $P_{1B}P_{2B}$, line segment>, < $P_{1A}P_{2B}$, line segment>]; [overlap, < $P_{1A}P_{2A}$, line segment>, < $P_{3B}P_{4B}$, line segment>, < $P_{3B}P_{2A}$, line segment>]]. Therefore, the last element ζ in the matrix is an effective complementary for the description of topological relations of two planar regions. In summary, a detailed representation of topological relations of two planar regions consists of SRp and topological matrix with ζ.

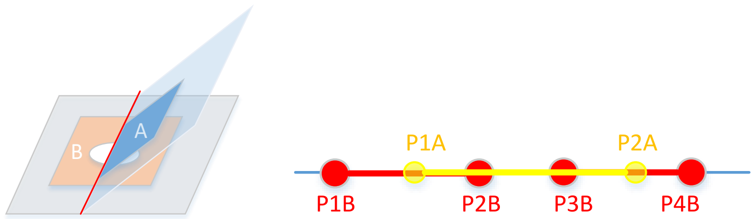


Figure 4-2 Topological relations of two planar regions with holes

4.5.2 Definition of Topological Relations between Planar Regions

In the following section, we present some examples for disjoint, meet and intersect relations and their representations. One should note again that the intersection relation contains different cases of the relations between two planar regions as presented in the previous section.

4.5.2.1 Disjoint:

According to the definition of disjoint relation in 9IM, $\text{disjoint(A,B)} = [-1\,-1\,*;-1\,-1\,*;*\,*\,\zeta]$ is used to decide disjoint relation between planar regions in R^3. However, there are several cases for the disjoint relation between two planar regions in R^3. For example, in Figure 4-3(3) and 3(6), the relations between A and B are represented with the same element ζ. But combining other eight elements in the matrix, ζ can be used as a key element to differentiate those cases in R^3.

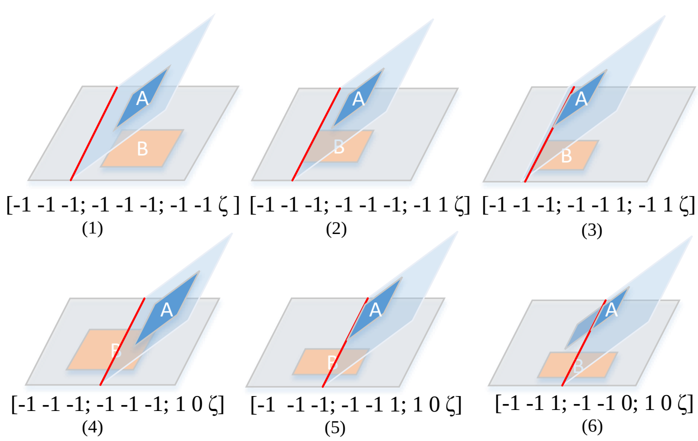


Figure 4-3 Disjoint relations of two planar regions

4.5.2.2 Meet:

For a meet relation, there are six common cases that we can distinguish. In Figure 4-4(1), ζ is the case of meet relation. In (2), (3) and (4), they have the same previous eight elements in the matrix, but ζ is various. They are overlap, equal and contain relations respectively. But in (1), (5) and (6), they have the same ζ.

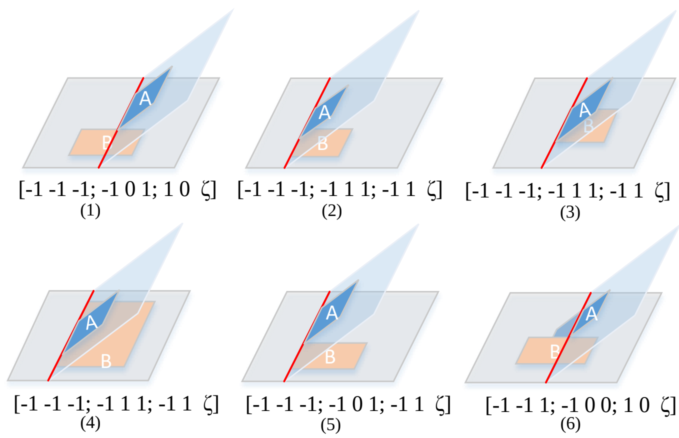


Figure 4-4 Meet relations of two planar regions

4.5.2.3 Intersect:

The following six cases are common relations for the intersection relations between two planar regions. In Figure 4-5(1) and (4), two ζ representations are the overlap case. For (2) and (5), they are the equal case. In the same way, ζ in (3) and (6) are the contain case.

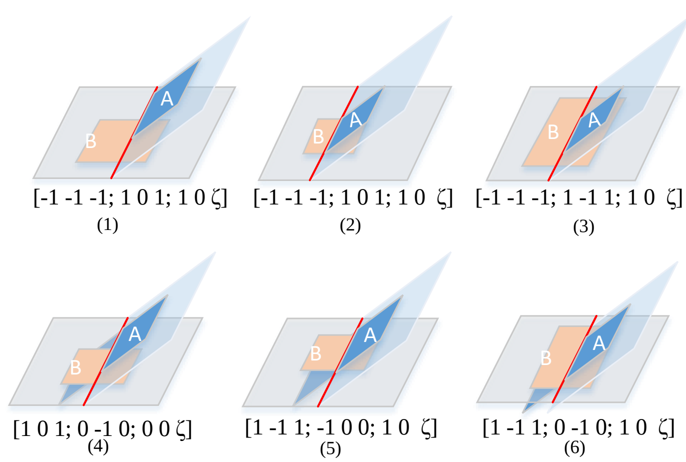


Figure 4-5 Intersect relations of two planar regions

4.5.3 The Discriminant of Topological Relations between Planar Regions

The discriminant of topological relations between planar regions needs four steps:

Step 1: Compute parameters of plane equations for two planar regions in a same Cartesian coordinate system in R^3;

Step 2: Compute the spatial relations of planes (SRp);

Step 3: Decide the topological relations between planar regions based on SRp;

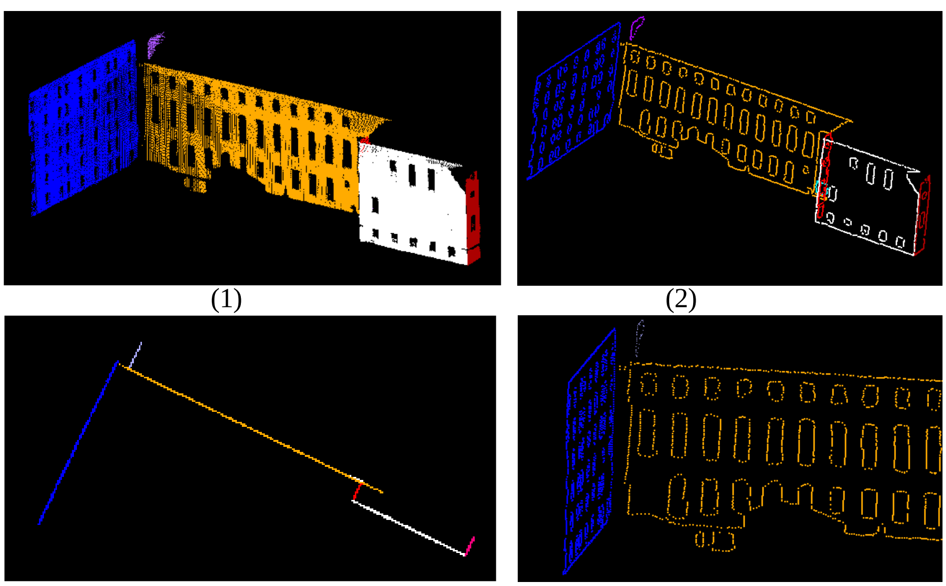
- If SRp is parallel, topological relations of planar regions (TRr) is disjoint;
- If SRp is coplanar, TRr is the case of topological relations between regions in 2D space;
- If SRp is intersecting, firstly, calculate the intersecting line equation of two planes and decide the common parts of planar regions and intersecting line; then, compute the elements of the topological matrix, including the last element ζ as described in the previous section;

Step 4: Provide semantic descriptions topological relations after geometric computation and analysis of matrix;

The first three steps are done by geometric computation. In the third step (c), the topological relations can be defined by a 2*2 submatrix $T_{2\times 2}(A,B)=\begin{bmatrix}\dim(A^\circ\cap B^\circ) & \dim(A^\circ\cap\partial B)\\ \dim(\partial A\cap B^\circ) & \dim(\partial A\cap\partial B)\end{bmatrix}$ in the upper left of $T_p'(A,B)$. For the disjoint case, $T_{2\times 2}(A,B)$ = [-1,-1; -1,-1], it is same as the case in 2D space. For the meet case, $T_{2\times 2}(A,B)$ = [-1,-1; -1, *], here * could be 0 or 1. According to the matrix $T_p'(A,B)$, the intersect case can also be decided by matching the elements from matrixes in Figure 4-5. Additionally, for each case, ζ can be defined and stored following the predefined formats in section 4.5.1. The detailed intersected information is described in ζ. If there are more than one list ζ_i in ζ, it indicates that there are holes that pass the intersecting line. The common part in ζ is the connection part of two planar regions. Therefore, the topological relations between two planar regions in R^3 are obtained through the geometric computation and the predefined matrix to describe topological relations and the connection of planar regions.

4.6 Challenges for Extraction of Topological Relations between Planar Regions Obtained from Point Cloud

Point clouds can be observed by Light Detection And Ranging (LiDAR) devices, including terrestrial and airborne LiDAR. In a point cloud, information is contained in high volume points. Each point has several attributes defining coordinate (x, y, z), intensity, classification, number of returns and point source ID and so on. However, despite the high density of points from surfaces, for occlusion cases, there may be missing parts in scanned LiDAR data that lead to incomplete segmentation of objects components. This can affect the determination of boundaries of each component of 3D complex object. Each component can be represented as a planar region and be used for obtaining topological relations between those components. For example, a wall could be modelled as a rectangle planar region. However, the boundary extracted from point clouds is not a perfect rectangle. A concave polygon extracted from a component cannot be directly estimated as a rectangle because the boundary constituted by points of a concave polygon is difficult to be ensured to form line segments of rectangles perfectly. As shown in Figure 4-6(1), following the segmentation step, six segments are identified in the point cloud for defining the building walls. From the top view in Figure 4-6(3), these segments look to be connected together perfectly. However when the boundaries of those segments are extracted, their topological relations are not perfect. We can see several gaps between the blue part and yellow part (Figure 4-6(2) and 6(4)). These imperfections affect the extraction of final boundaries and the determination of topological relations between those segments. Besides, the boundaries quality also depends on the quality of the point cloud. Thus, boundaries of components cannot be directly modelled as some primitives. In sum, extracting topological relations among components of a complex 3D object obtained from 3D LiDAR point clouds is very complex. Because the planar regions are not perfectly embed in a plane as supposed in the previous sections. The boundaries of those regions are very irregular and composed of concave hulls of points composing the region. These may become more complex if we deal with occlusion presence in point clouds.



(1) (2)

(3) (4)

Figure 4-6 Examples of the components of a building and their boundaries obtained from a point cloud

4.7 Experimental Analysis

In the automatic modelling from point clouds, the existing segmentation algorithms can detect planar components from point cloud because the model-based geometric detection algorithms are capable of detecting planes and acquiring parameter of planes from point clouds. For example, Random Sample Consensus can segment simple primitives, such as planes, spheres, cylinders and cones. After segmentation, in Figure 4-7(1), 16 pieces of planar components are extracted from a building. From the top view of the building, lines with different colours indicate different walls. In Figure 4-7(2), this building is displayed from another view. Five walls of this building are presented in Figure 4-7(3). Each segment has geometric properties after segmentation. For example, a segment can be represented by geometric parameters (A, B, C, D) for a plane equation. We use the equations of two planes in 3D space to determine the equation of their intersecting line (L). Consider that $a_1X + b_1Y + c_1Z + d_1 = 0$ and $a_2X + b_2Y + c_2Z + d_2 = 0$ to be two plane equations. The direction vector of the line L is orthogonal to the normal vectors of two planes $n_1 = (a_1, b_1, c_1)$ and $n_2 = (a_2, b_2, c_2)$. The direction vector is obtained by $s = n_1 \times n_2$. If $M(x_1, y_1, z_1)$ is a common point between the two planes then the line equation is defined as:

$$\frac{X - x_1}{p} = \frac{Y - y_1}{q} = \frac{Z - z_1}{r} \qquad \textbf{(Eq 4-6)}$$

Where $p = b_1 * c_2 - b_2 * c_1$, $q = c_1 * a_2 - c_2 * a_1$, $r = a_1 * b_2 - a_2 * b_1$

To determine the common parts of two planar regions and the intersecting line, the distance between points of planar regions and line is used to make a decision. The distance between a point $M_0(x_0, y_0, z_0)$ and the line L in 3D space can be computed by the following equation:

$$d^2 = (x_0 - x_1)^2 + (y_0 - y_1)^2 + (z_0 - z_1)^2 - \frac{[p(x_0 - x_1) + q(y_0 - y_1) + r(z_0 - z_1)]^2}{p^2 + q^2 + r^2} \qquad \textbf{(Eq 4-7)}$$

In order to compute the value of ζ, we need to determine if both planar regions have interstation with line L. To do so, we define a distance threshold which is determined by the average distance between M and its K-nearest neighbours. Thus, each point in the planar regions has its distance threshold to judge whether it is on the line. By considering the K-nearest neighbours of M, we make sure that the distance is determined based on the local density of points. Here K is defined by the density of point cloud. If the distance between point M belonging to one of the regions and the line L is less than the threshold of this point, then we consider that this point is on the line L. Next, those points belonging to one of the planar regions on the line L are combined to create line segments using the same distance threshold used in the previous step. If the distance between point M and its nearest boundary point N on the line are in the distance threshold of M, M and N are added to the same line segment. In the next step, N is the new starting point to search other points on the line. This action is repeated until all the points of a planar region are processed. In this way, the line segments formed by the common part of the intersection line L and the planar region are obtained. This process is also carried out for the second planer region in the same way. The points of planar regions have two classes: boundary and interior. Therefore, the line segments are easy to be identified as the intersecting part of line L and the boundary or the interior. Finally, the line segments belonging to two regions on the line L are used to determine ζ according to the steps presented in Section 4.5.1.

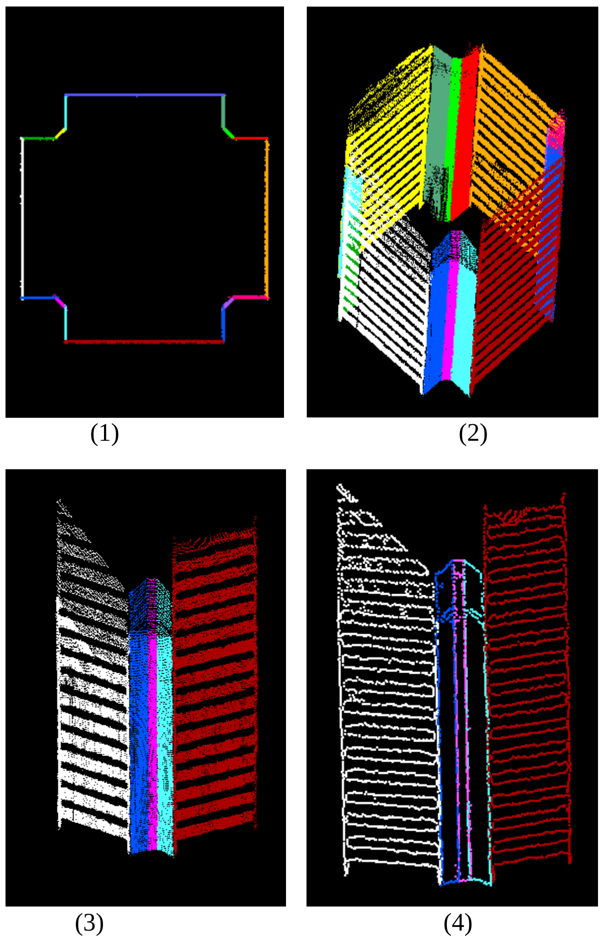


Figure 4-7 Results for planar regions segmented from point cloud

For distinguishing the boundary and interior of each segment, the concave hull of a planar segment is extracted from the point cloud, which is implemented by algorithms in Point Cloud Library (Rusu, 2011). As shown in Figure 4-7(4), the white planar region and blue one have the meet relation, similarly, the pink one has meet relation with the blue one. These relations are computed using the topology matrix following the steps presented in Section 4.5.3. Therefore, the topological relations between two neighbouring segments are obtained by the topology matrix and the last element ζ .

4.8 Conclusion and Future Work

The topological relations between planar regions in R^3 are extended from Dimension Extended 9-Intersection models. The extended model is more expressive and allows better distinguishing and describing the topological relationships among planar regions. Furthermore, it can transform geometric information into topological relations between components of 3D complex objects based on basic geometric computations and the analysis of topology matrix. The proposed approach describes not only the topological relations, but also the details of the relation of the connection parts between planar regions. Moreover, the topological relations of planar regions with holes can be represented by the proposed approach. We have also analysed different challenges that we have when applying the proposed method for the determination of topological relations between two planar regions extracted from point clouds. Finally, the proposed topological models is applied to identify the topological relations between planar regions extracted from point cloud automatically. Future work will be focused on extending topological relations of planar regions to other geometric primitives. Also, the data structure for topological relations of objects components will be designed to realize spatial querying and analysis on complex 3D objects. Furthermore, we will explore the creation of complete B-Rep models based on fundamental topological relations in 3D complex models.

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Introduction of Article

A Knowledge Base for Automatic Feature Recognition from Point Clouds in an Urban Scene

Feature recognition is helpful to identify the semantic information of objects and their components. Knowledge about objects in urban scene is the bridge of linking the semantic of urban scene and the quantitative information extracted from point clouds. In Chapter 5, automatic feature recognition of objects in urban scene are proposed by integrating knowledge about objects. As shown in the following figure, segmentation results of objects are imported into knowledge base as individuals with properties and topological relations between object components are formalized as relations between individuals. The information extracted from point clouds based on work in previous chapters is considered as facts to infer semantic information of object and their components. Based on the knowledge formally represented as semantic rules in the knowledge base, semantic reasoning can infer the semantic information of objects, such as building components and building roof style.

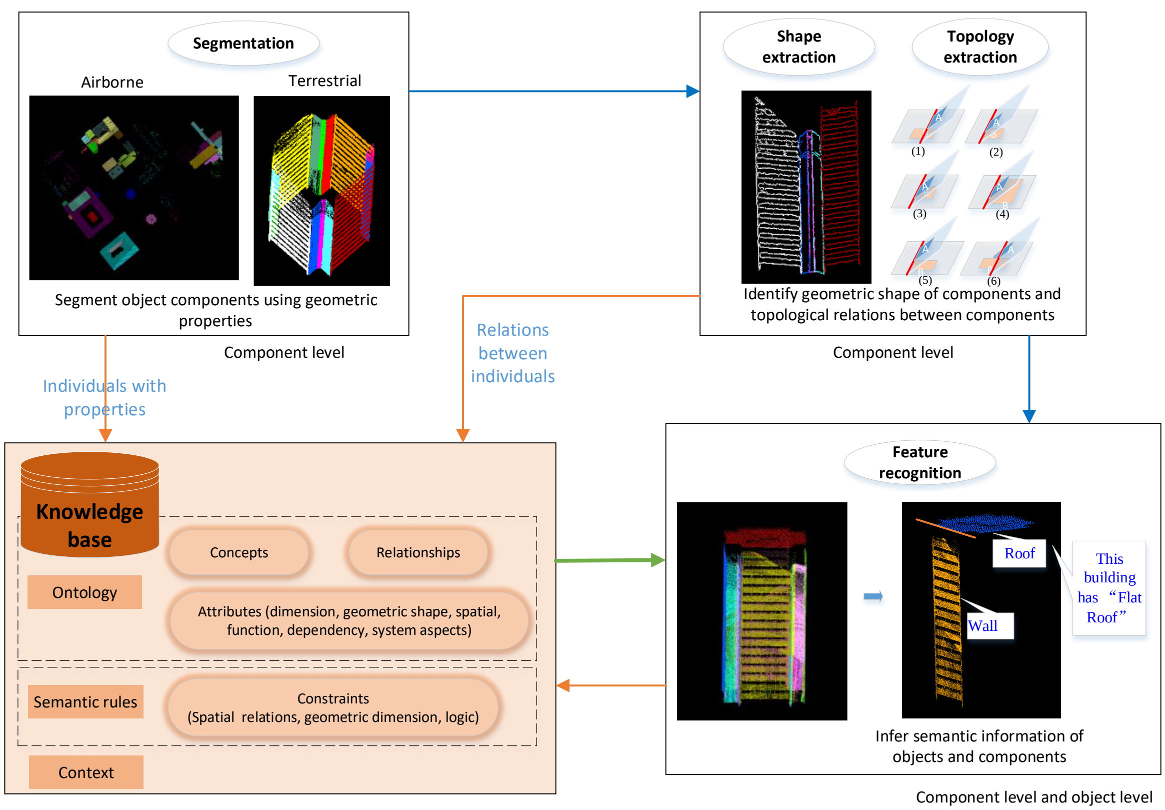

Figure VII the work expected to be done in feature recognition based on knowledge

In the following article, a knowledge base is proposed for automatic feature recognition from point clouds in an urban scene. The concepts of objects in an urban scene are defined and identified from different perspectives including geometry, architecture, functionalities and nature of objects, which make it possible to describe a complex urban scene. The properties of concepts and their relations are defined after the consideration of the need for automatic feature recognition. Based on our proposed segmentation solutions and the proposed model for formalizing topological relations of complex object components in 3D space, object components extracted from point clouds are transformed into the individuals of concepts in the knowledge base. Thus, the proposed knowledge base can be used to reason semantic information of object components. Then the knowledge base is evaluated by answering the competency questions including reasoning complex geometries composed of planar segments, representing a complex roof style, reasoning the roof shape from point clouds and reasoning building components from an incomplete point cloud caused by occlusion. In the experiment, some rules are defined based on the concepts, formalized topological relation and properties in the knowledge base. The reasoning step is conducted for answering the above competency questions.

CHAPTER 5 A Knowledge Base for Automatic Feature Recognition from Point Clouds in an Urban Scene

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5.1 Résumé

La technologie LiDAR peut fournir des informations géospatiales très détaillées et précises pour une scène urbaine afin de créer des environnements géographiques virtuels (VGE) pour différentes applications. Cependant, la modélisation 3D automatique et la reconnaissance des caractéristiques à partir des nuages de points LiDAR sont des tâches très complexes. Cela devient encore plus complexe lorsque les données sont incomplètes (problème d'occlusion) ou incertaines. Dans cet article, nous proposons de construire une base de connaissances comprenant une ontologie et des règles sémantiques visant la reconnaissance automatique des caractéristiques à partir de nuages de points pour la modélisation 3D. Premièrement, plusieurs modules d'ontologie sont définis à partir de différentes perspectives pour la description d'une scène urbaine. Par exemple, le module de relations spatiales permet la représentation formalisée d'éventuelles relations topologiques extraites de nuages de points. Ensuite, une base de connaissances est proposée. Elle inclut de différents concepts, leurs propriétés et leurs relations, ainsi que des contraintes et des règles sémantiques. Par la suite, les instances et leurs relations spécifiques forment une scène urbaine et s'ajoutent à la base de connaissances en tant que faits. Sur la base des connaissances et des règles sémantiques, un processus de raisonnement est exécuté pour extraire les caractéristiques sémantiques des objets et de leurs composants dans la scène urbaine. Enfin, plusieurs expériences sont présentées pour montrer la validité de notre approche pour reconnaître différentes caractéristiques sémantiques des bâtiments à partir de nuages de points LiDAR.

5.2 Abstract:

LiDAR technology can provide very detailed and highly accurate geospatial information on an urban scene for the creation of Virtual Geographic Environments (VGEs) for different applications. However, automatic 3D modeling and feature recognition from LiDAR point clouds are very complex tasks. This becomes even more complex when the data is incomplete (occlusion problem) or uncertain. In this paper, we propose to build a knowledge base comprising of ontology and semantic rules aiming at automatic feature recognition from point clouds in support of 3D modeling. First, several modules for ontology are defined from different perspectives to describe an urban scene. For instance, the spatial relations module allows the formalized representation of possible topological relations extracted from point clouds. Then, a knowledge base is proposed that contains different concepts, their properties and their relations, together with constraints and semantic rules. Then, instances and their specific relations form an urban scene and are added to the knowledge base as facts. Based on the knowledge and semantic rules, a reasoning process is carried out to extract semantic features of the objects and their components in the urban scene. Finally, several experiments are presented to show the validity of our approach to recognize different semantic features of buildings from LiDAR point clouds.

Keywords: LiDAR; feature recognition; urban scene; ontology; knowledge base; semantic reasoning

5.3 Introduction

Virtual Geographic Environments (VGEs) are a new generation of geospatial technologies providing advanced modeling, simulation, and visualization capacities for better representation, analysis and understanding of the complex geographic world (Lin, 2013a; Lin, 2013b). Construction of virtual geographic environments for urban scenes allows better understanding of diverse static and dynamic geographic phenomena, including urban development, traffic (Li, 2015), air pollution (Xu, 2011; Xu, 2013), crowd behavior (Torrens, 2015), urban planning, etc. Geometrically precise and semantically enriched representation of geographic environments allow spatial reasoning such as navigation and path planning based on Multi-Agent Geo-Simulation in VGEs (Mekni, 2010). LiDAR technology makes it possible to observe real-world environments rapidly and record very detailed geographic information in the form of point clouds in support of the generation of precise 3D VGEs. However, automatic 3D modeling and feature recognition from LiDAR point clouds are very complex tasks. This becomes more complex due to the presence of occlusion problems, and uncertainty in the data.

In general, automatic 3D modeling from point clouds implies: (1) classification of points belonging to the same object; (2) segmentation of objects and their components; (3) definition of relations between objects components; and (4) recognition of object types and their components. Extraction and recognition of objects from a point cloud imply not only the extraction of geometric features of the object (geometric primitives, size, shape, borders, etc.) but also involve their semantics. We will refer to the latter as semantic feature extraction throughout this paper. Semantic and geometric features are then two complementary sets of knowledge that we need to extract and recognize different object types from point clouds. Object extraction and recognition requires the integration of semantic features with geometric features. For example, a planar segment extracted from point clouds could represent a wall, a component of a roof or a part of the road. Assigning the right semantics to geometric objects detected in a point cloud is a complex task.

Recently, knowledge-based solutions have been introduced to support automatic 3D modeling and object recognition from LiDAR point clouds. For example, knowledge of size, shape, position, orientation, topological relations between building components as well as physical properties, such as color and texture, can be used to recognize and model its components such as walls, doors, roofs, and windows (Pu, 2009). Semantic network technologies are also employed to describe potential relations between different components of buildings (Tang, 2010). Indeed, the topological relations between the components of objects with complex structures are essential to identify semantic features of objects with varying topologies among components, for example, complex geometries and roof shape. Additionally, the recognition of higher-level semantic features (such as the architectural styles of buildings) requires more detailed qualitative knowledge. Semantic reasoning based on this knowledge would be essential for their modeling and recognition.

Ontologies can formally represent knowledge of spatial objects. Ontology is defined as the specification of conceptualizations that helps to make information communication and sharing among programs and humans more efficient (Gruber, 1995; Guarino, 1995a). It can be represented as a set of logical axioms to explain the intended meaning of a concept (Guarino, 1998). For sharing information in automatic 3D modeling, the formalized representation of knowledge is an essential step in building a knowledge base. An ontology can be represented as a semantic network, which is a graph where vertices indicate concepts and edges describe the relations among those concepts. For machine processing, more specialized formalization of knowledge, such as Resource Description Framework (RDF), Web Ontology Language OWL and Semantic Web Rules Language (SWRL), is needed for representing knowledge, defining rules and carrying out semantic reasoning on the knowledge.

Knowledge-based solutions are increasingly used to improve the accuracy, and the quality of results, especially for feature recognition in the automatic 3D modeling from LiDAR point clouds (Cantzler, 2003; Pu, 2009; Rusu, 2009b; Tang, 2010). However, there are still challenges for automatic 3D modeling and object recognition from point clouds in a complex urban scene. These challenges include the diversity of object types, the complexity of their shape and their spatial relations.

In this paper, we propose a knowledge-based approach for automatic object recognition from LiDAR point clouds in urban scenes. First, we define several modules for the ontology to organize concepts describing an urban scene from different perspectives. The main components of the ontology, including concepts, properties, and relations, are designed to take into account the requirements of automatic feature recognition from point clouds. More specifically, we have integrated formalized information on objects and their relations, which allows us to reason on both geometric and semantic features of objects at different levels of detail. Hence, the main contribution of this paper is automatic recognition of objects and their components based on reasoning on their geometric and semantic features that are formally represented and described in a knowledge base. In order to demonstrate the validity of the proposed approach, we present a case study for automatic recognition of semantic features of buildings from point clouds. For this purpose, prior knowledge of related concepts, their properties and relations, as well as a set of semantic rules, has been defined and included in a knowledge base and the reasoning results have been presented and discussed.

We expect that the approach proposed here in this paper can be extended to help the recognition of any type of object and its components in an urban scene. However, for the sake of simplicity and in order to show the potential of the proposed knowledge base, we have focused our experiments on the recognition of buildings and their components. In this case, we have a man-made object composed of simple planar segments where the extraction of properties and relations from point clouds are relatively simpler. This is also true for the definition of the rules to support a reasoning process using the knowledge base.

The remainder of this paper is organized as follows: Section 2 investigates the existing knowledge-based methods for automatic 3D modeling and feature recognition and the solutions of using ontologies in practical applications. Section 3 presents the motivations for building a knowledge base for automatic 3D modeling. Then it describes in detail our proposed conceptual framework for this purpose and defines the scope of the proposed knowledge base and its content. Section 4 presents a case study for the evaluation of the proposed approach. Finally, Section 5 presents conclusions and perspectives for future works.

5.4 Related Works

Current approaches for 3D modeling from point clouds are mostly based on geometric approaches and are not sufficient to create complete and semantically enriched 3D urban scene models and virtual geographic environments from point clouds. An urban scene can be described using both quantitative and qualitative information on objects and their relations. Objects can be described by their geometric features (length, width, height, area, shape, boundary, etc.), and their geometric relations (parallel, perpendicular, coplanar), as well as their topological and logical relations. Any additional specification and constraints defining the properties and relations of an object are essential for efficient object recognition in the scene. Geometric features can be extracted from point clouds. However, semantic feature extraction is more complex and needs semantic reasoning on the entire knowledge including the extracted information from point clouds as well as the prior qualitative knowledge of the urban scene and its objects.

Knowledge of geometric relations can help 3D modeling and the extraction of semantic features of objects in an urban scene. For example, reasoning on geometric relations to determine the connections between the components of man-made objects is helpful for the creation of 3D geometric models from point clouds. There are two approaches to reason on geometric relations, deductive and algebraic reasoning (Loch-Dehbi, 2011). For example, Loch-Dehbi et al. (Loch-Dehbi, 2011) introduced an algebraic method to demonstrate that constraints are deducible within sets of premises, aiming to support the interactive 3D city modeling and the automatic reconstruction of objects such as buildings and their components. The method is also capable of extracting geometric relations from uncertain observations. For the automatic feature extraction from a complex urban scene, the deductive and algebraic reasoning methods can be used to determine geometric relations between components extracted from point clouds. These relations can be represented as formal expressions such as “isParallelTo”, “isPerpendicularTo” in a knowledge base and used with other information for the extraction of semantic features on objects in subsequent steps.

Knowledge-based solutions have been proposed for the identification of the semantic meanings of objects from point clouds. Pu et al. (Pu, 2009) introduced a knowledge-based method for the reconstruction of building facades from terrestrial LiDAR data. In this study, information derived from point clouds such as size, position, orientation and topology is used to recognize building components, such as walls, doors, roofs, protrusions, intrusions, and windows. In addition, the fact that LiDAR cannot detect glass is used for the recognition of doors and windows in the point cloud. In other studies, knowledge-based approaches are proposed for the recognition of railway facilities from point clouds (Hmida, 2012b; Truong, 2013b). Further studies have attempted to label indoor components of buildings (Xiong, 2013) and identify objects in kitchen environment (Rusu, 2009b) through learning algorithms. However, these methods are still very limited for the cases where we have many types of object to be detected and recognized at different levels of detail.

Prior knowledge of an urban scene must be formally defined and represented in a knowledge base. Ontologies have been employed for knowledge representation in many practical applications. For instance, ontologies describing railway facilities are used together with 3D modeling algorithms for processing point clouds to guide 3D object detection and labeling (Hmida, 2012b). In (Truong, 2013a), authors employ an ontology with a set of semantic rules to select algorithms and related parameters for detecting specific types of objects in a point cloud. In other fields, ontologies are used for better representation, sharing and reuse of spatial data. An ontology is presented for searching the most appropriate work automatically according to work conditions for avoiding subjective decision-making in the field of construction (Lee, 2015). As another example, knowledge about safety management and construction risk is represented as an ontology for the development of a knowledge-based risk management system (Zhong, 2014). The ifcOWL is proposed for connecting semantic web technologies and the IFC standard in the construction industry (Pauwels, 2017; Pauwels, 2016). For mobility requirements, ontologies are used to support indoor and outdoor navigation systems developments (Isikdag, 2013; Shayeganfar, 2008). These examples show the potential of ontologies for better representation of knowledge in an urban scene in support of object recognition in a LiDAR point cloud.

In summary, for automatic recognition of semantic features of objects in support of the construction of 3D urban virtual geographic environments, an ontology of an urban scene is necessary to formally represent knowledge about objects in the scene. Semantic information on an urban scene can be formalized and represented in a knowledge base, and semantic rules can be added to allow reasoning on semantics of objects and their relations in support of 3D modeling and object recognition from point clouds.

5.5 Building a Knowledge Base for Automatic Feature Recognition

In philosophy, ontology is designed to explain the nature and relations of all beings, and it does not depend on a particular language (Guarino, 1998). In the domain of Artificial Intelligence (AI), ontology refers to knowledge representation, consisting of terminologies of a specific domain to describe certain realities that usually is conceptualized as concepts and their relationships (Guarino, 1998; Hadzic, 2009). Ontology is preponderant to represent and formalize the domain knowledge and experience for knowledge sharing and reuse (Gruber, 1995). If necessary, some rules are integrated to explain the activities of concepts. In the domain of 3D urban modeling, ontology is employed to formally represent knowledge about urban scenes, including concepts, names, properties, and their relations with other concepts. Then, semantic rules designed based on these concepts are integrated into the ontology to build a knowledge base for automatic feature recognition.

In general, ontologies are classified into top-level ontologies, domain ontologies and task ontologies, and application ontologies (Guarino, 1997; Guarino, 1998). Top-level ontologies describe general concepts such as space, time, matter, object, event, action, etc. that are independent of a specific domain. Domain and task ontologies aim at generic domains and tasks. The related terms and vocabularies for generic domain, generic task or activity are defined. The semantic meanings of terms are additionally stated in certain domain and task, which is a process of specializing the terms in the top-level ontology (Guarino, 1997). Application ontologies represent concepts in a concrete domain, and the concepts are specialized continually in specific applications. They are designed for describing particular domain entities or a certain activity (Guarino, 1998). Therefore, choosing the appropriate level of ontology is important before developing an ontology because it indicates what concepts and relations should be considered to be included in the ontology and what would be their definitions and their specification.

An ontology is an abstraction of reality. The mismatch between an ontology and reality that it describes will appear if the concepts are not well specified. When specific vocabularies are used to explain the concepts in certain domains, the ontology closely depends on the language that is used. In other words, the expression scope, and the meaning of vocabularies and terms decide the accuracy of describing realities. Hence, minimal ontology commitment is an important criterion in developing an ontology (Gruber, 1995). Also, building an ontology does not aim to reason knowledge at the domain level. However, it attempts to help to understand the underlying knowledge with a computer-interpretable format in the practical applications. Thus, defining the ontology scope is a major step before developing an ontology. This allows the ontology to accurately represent concepts and their relations that are abstract of the physical objects and relations in a specific domain.

In this paper, we apply ontologies to represent the knowledge about objects in an urban scene and then to extract semantic features of objects by reasoning on the prior knowledge provided on a scene. The knowledge of an urban scene may include different concepts and their properties from architectural domain (terms of architecture, building components and their relations), geometry (the definition of geometric primitives and their geometric relations), and their topological relations (topological relations between objects and among their components). The ontology designed for automatic feature recognition is positioned as an application ontology. The scope of the ontology is defined so that it can help the classification of object types, and the extraction of semantic features of objects and their components from point clouds of urban scenes. Based on the METHODOLOGY approach presented in (Fernández-López, 1997; Grüninger, 1995), we used the following steps in the development of our ontology:

- identification of motivating scenarios and the scope of the ontology;
- definition of competency questions;
- building the ontology (ontology capture, ontology coding and integrating the existing ones);
- validation of the ontology according to the requirements set by competency question;
- maintenance of ontology after verification.

Based on these steps, our motivation for building the proposed ontology is to realize automatic feature recognition from point clouds. The ontology should represent the formalized knowledge of objects in an urban scene. Then we use semantic rules to reason on the knowledge provided on the urban scene to recognize semantic features of objects obtain from segmentation results. The validation of its scope will be conducted by the experiments for the extraction of semantic features of objects in a given urban scene. The maintenance of an ontology in its life cycle is an evolving process. The ontology needs to be maintained and updated continually after implementation based on the evaluation of ontologies (Fernández-López, 1997). In our application, the ontology supports the extraction of geometric features of objects at the first level and then it supports their recognition. For the implementation of this ontology, the knowledge acquisition is conducted from multisource. Hence, integrating existing ontologies is acceptable in the process of building ontologies (Fernández-López, 2002). Next, the expected achievements of the built ontology are represented as competency questions, such as the recognition of complex geometric shape based on planar segments and the identification of building roof shapes from point clouds. After building the ontology, it is integrated into a knowledge base together with a set of semantic rules. These rules are used to reason on the knowledge to answer the competency questions. This will help to validate if the ontology is competent to solve the problems mentioned in motivating scenarios.

5.5.1 Conceptual Framework for Automatic 3D Modeling and Feature Recognition from Point Clouds of Urban Scenes

In our proposed conceptual framework, the task of automatic 3D modeling and feature recognition from point clouds of urban scenes is divided into five main steps: object detection, object recognition (point clusters forming an object), segmentation, feature recognition and 3D model generation by connecting the components of objects (as shown in Figure 5-1).

The process of determining the range of the subset that belongs to a single object in the point cloud is usually called object detection (Dorninger, 2007; Wang, 2007b). The clustering algorithm uses Euclidian distance to cluster the points belonging to a single object (Rusu, 2011).

In the object recognition, the object types are roughly classified according to the geometric properties of objects and by the reasoning on the geometric features of the concepts in the knowledge base. The purpose of object recognition is to select the segmentation algorithms to segment specific object types. In this step, the knowledge about different types of objects is provided by the knowledge base.

The aims of segmentation for a single object are to partition points into simpler groups, to decrease the search range, to reduce the computational cost and to simplify or alter the representation as segments that are more meaningful and easier to analyze (Dorninger, 2007; Shapiro, 2001). Segmentation operation aggregates points with similar attributes or meaning into a single segment. Geometric features are usually used to segment point clouds to regular shapes. For instance, man-made objects in the urban area are mostly composed of regular geometric shapes (Jochem, 2009). Some parts of natural objects are also segmented as geometric primitives, for example, the shapes of the trunks of trees have cylindrical shapes. Moreover, segmentation allows the extraction of some semantic features on objects that can be added to the knowledge base for further reasoning on objects and their components as well as their relations.

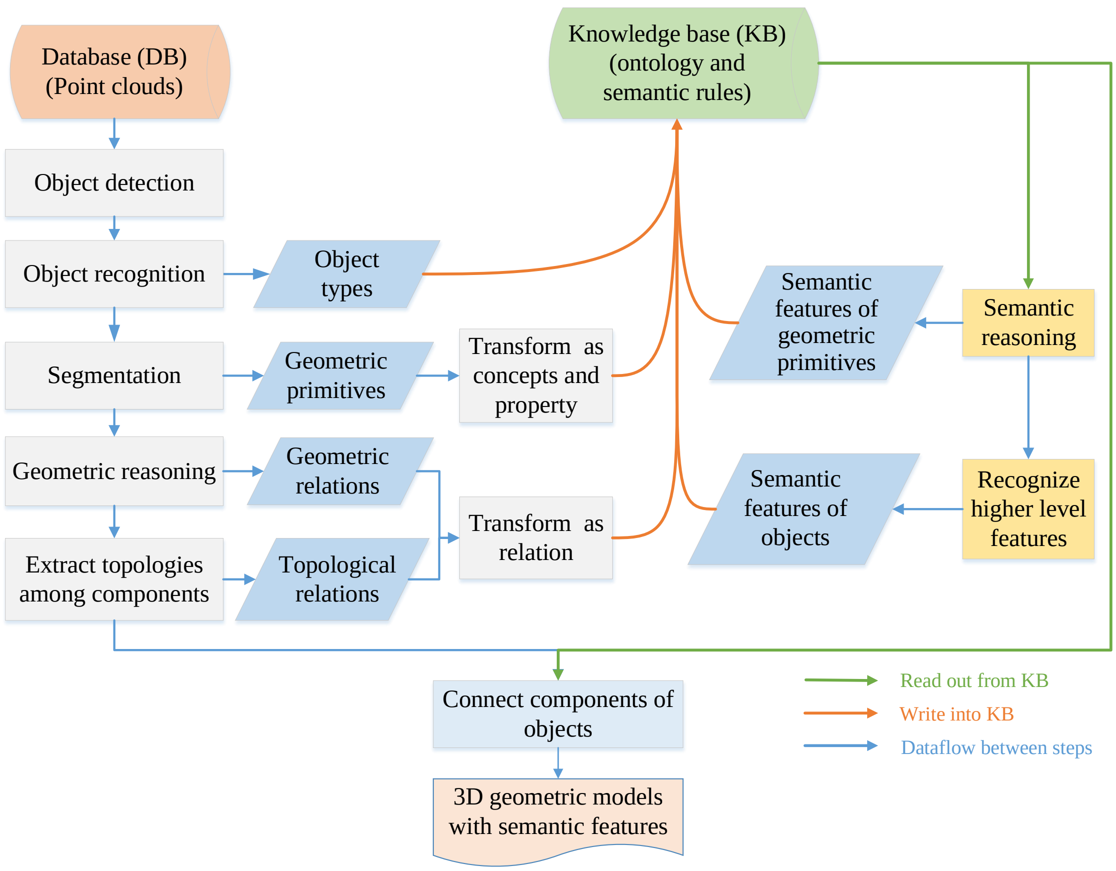


Figure 5-1 Proposed conceptual framework for automatic 3D modeling and feature recognition from point clouds.

In the feature recognition step, we need both quantitative and qualitative information on segmentation results for recognition of semantic features of objects. The extractions of geometric features including geometric properties, geometric relations, and topological relations are viewed as sub-steps of feature recognition. The segments are modeled as the instances of concepts or their components in the ontology. The information obtained from segmentation results is integrated into the knowledge base to enrich knowledge of object types as well. Based on the concepts and their relations, semantic rules are defined. These rules are used to discriminate different types of objects and to extract semantic features of objects. Therefore, the knowledge base representing the knowledge of objects in urban scenes is the core element for feature recognition. In this paper, we will focus on recognizing semantic features of objects automatically from segmentation results using the knowledge base.

In the 3D geometric model creation step, the components of objects are combined to create 3D geometric models based on segmentation results and the topological relations between them. Semantic features of objects obtained in previous step can be used to improve the completeness of 3D geometric models in accordance with the constraints among the semantic features of the objects.

In the proposed conceptual framework for automatic 3D modeling and feature recognition, the knowledge base composed of ontology and semantic rules is a vital component to the proposed approach. The formalized knowledge supports the reasoning process for the extraction of semantic features of objects. Therefore, the construction of the knowledge base motivates building of a core ontology for representing the knowledge of urban scenes. Reasoning on the knowledge provided in the knowledge base allows the extraction of semantic features to support objects recognition and 3D modeling process.

5.5.2 Definition of Concepts

Reasoning on objects embedded in an urban scene necessitates the extraction of quantitative (such as geometric dimensions, coordinates) and qualitative properties (geometric shape, surface type, geometric relations, dependency, topologies, functions, surrounding attributes, etc.) from a point cloud and its integration as facts in the knowledge base. Facts on objects are obtained from segmentation operation. This operation can be conducted using region growing method based on robust normal estimation (Nurunnabi, 2015) and Random Sample Consensus (RANSAC) algorithms (Rusu, 2011). The semantic features of objects are expected as output. These facts are obtained based on the concepts, their properties, and their relations defined in the ontology. Formal representations of this information are crucial for the knowledge base. Because formalized representations of the knowledge are necessary to conduct semantic reasoning. Semantic reasoning uses facts and semantic rules to produce new knowledge of the object in the urban scene.

Hence, identification of different concepts, their properties, and their relations is fundamental for the building of an application ontology that will be used to support automatic 3D modeling and feature recognition in an urban scene. Table 5-1 presents different properties and relations that are included in the definition of different concepts in our ontology.

Concepts of an ontology describing an urban scene can be organized in a hierarchical manner using a graph structure. It is also possible to organize the concepts based on different views. A well-balanced ontological hierarchy gives a comprehensible representation of domain knowledge (Gavrilova, 2005). Some tips could be helpfully considered to formulate the balanced hierarchical conceptual tree. For example, concepts should be linked with a single relationship (is-a, is-part-of), the depth of the tree should be around equal, and cross-links should be as little as possible (Gavrilova, 2013). Therefore, concepts described by multi-dimensional information is an expressive way to describe urban scenes.

Table 5-1 Detailed quantitative and qualitative properties in the ontology.

Information Type	Terms	Examples
Quantitative Elements	Geometric Dimension	length, width, height, radius, thickness, area, volume
	Geographic Coordinate	latitude, longitude, elevation
	Local Coordinates	X, Y, Z
	Properties of Point Clouds	intensity, return number, point source ID, classification, color
Qualitative Elements	Object Types	building, car, road, tree, pole, etc.
	Geometric Shape	circle, rectangle, ellipsoidal, cross-sectional shape, line, cylinder, cuboid
	Surface Type	plane, curved surface
	Dependence	logical dependence, geographic dependence, physical dependence
	Topology	2D and 3D topology
	Function Relevance	interrelated relation for functions
	Surrounding Attributes	the neighboring information and their relations
	Architecture Components	wall, roof, floor, door, windows, balcony, etc.
	Roof Shapes	flat, shed, gable, hip, barrel, etc.
	Material Attributes	concrete, wood, asphalt
	Geometric Relations	parallel, perpendicular, intersecting, coplanar, etc.

5.5.3 Modularity of Concept in an Urban Scene

Modularity is an effective means to decrease the complexity in engineering, such as software development in software engineering. In the design of an ontology, modularity is a generic way to keep ontologies small to ensure reasoning performance and maintenance in knowledge management (Stuckenschmidt, 2009). Concepts in an ontology can be categorized based on their types. In the lower level, an object is decomposed into its components. In the higher level, objects having similar function could be aggregated as a subsystem. In addition, the modules of spatial and topological relationships in ontologies are designed to represent the relations between objects and their components. Other modules, such as functionality, attributes, constraints, relationship, and axioms, are defined to describe the concepts and their relations.

Identifying the concepts and the partitions of modules are the most significant steps in building an ontology. Firstly, the definition of concepts with understandable way is summarized from the real world in the urban scene. The quantitative and qualitative information that could be extracted from the segmentation results of point clouds is essential to describe objects in the ontology. The definitions of concepts should take this information into account. Besides, the relation module for describing the relevant relations (such as geometric, topological and logical relations) among concepts is defined. Finally, objects can be described by their topological relations, functionality, and semantic features.

In the following subsection, several modules are defined to organize concepts in the ontology, based on elevation, functionality, the source of objects, geometry, composition, and spatial relations.

5.5.3.1 Elevation Perspective

Coordinates are the most fundamental spatial information in point clouds that define objects shape and position. A cluster of points for an individual object forms a meaningful label. The core principle of clustering algorithms is to find a cluster based on a set of specific criteria. In point clouds, the closer points are more related to each other. Therefore, the spatial distance is a criterion to cluster points belonging to the same objects.

Considering elevation property of concepts given by Z coordinates, objects can be classified into ground, near-ground and non-ground categories following the generic category of objects in point clouds defined in (Pu, 2011). For example, a road and a lawn belong to the ground class, curbs and small shrubs belong to the near-ground class, and buildings, trees, cars, and poles are categorized under the non-ground class. For defining building concept and its components, we benefit from concepts defined in the domain of architectural design (Hois, 2009). Based on the classification of elevation, road curbs are closely associated with the road surface, and they can be used to determine the local width of a road. The lawn can be regarded as a part of the ground. The module of elevation is designed as follows in Figure 5-2.

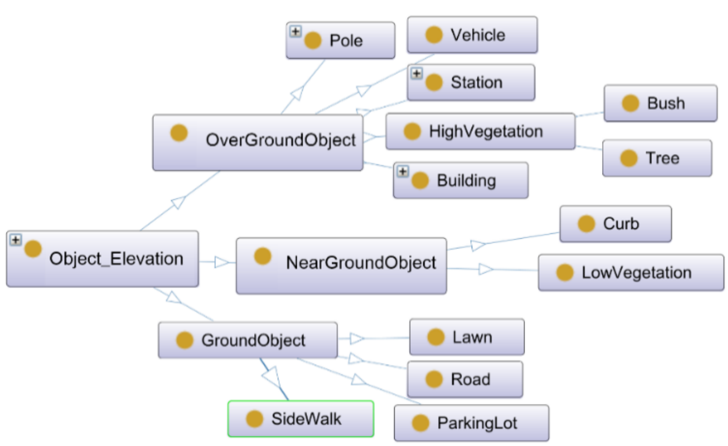


Figure 5-2 Classification of concepts according to the elevation perspective.

5.5.3.2 Functionality Perspective

Another perspective to modularize concepts in an ontology is based on objects' functionality and spatial proximity. For example, a building and a vehicle are all classified into non-ground objects based on elevation modularization. However, their functionalities are different as a building built for living and working while the vehicle is designed as a means for transportation purpose. From this point of view, objects in an urban area can be linked to the transportation system, and all function units are connected to the road. For example, buildings are individual functional groups, such as business buildings, residential, or school buildings. However, a parking area consists of a parking lot, poles for paying the parking fee, sign poles and some possible parked vehicles. Transportation system contains roads and associative supporting facilities (such as traffic sign poles, light poles, traffic lights pole and bus station). Also, lawn, trees, and bushes are parts of the landscape. A public square, an open area at the meeting of two or more streets, is comprised of a part of the ground. There may contain some plants, bushes or statues in some case. Finally, the main concepts in the functionality module are shown in Figure 5-3.

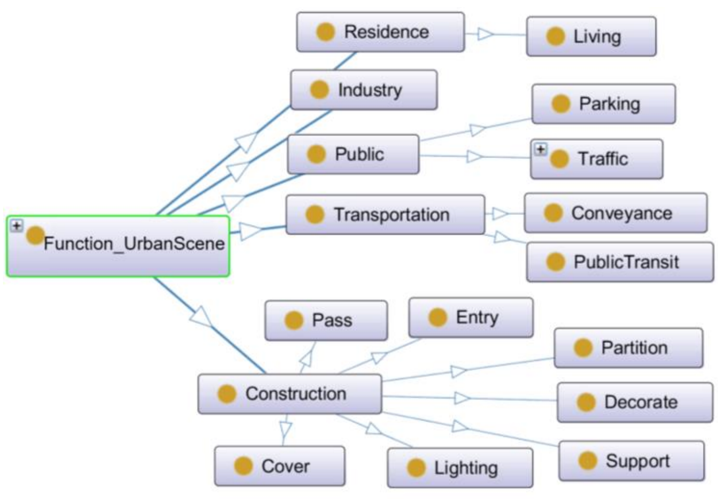


Figure 5-3 Classification of concepts according to functionality perspective.

5.5.3.3 Nature of Objects Perspective

Objects are either natural or artificial (man-made). From this perspective, trees, grasslands, bushes, etc. are classified as the plant in the class of natural objects. Roads, buildings, bridges, traffic poles, vehicles, etc. are placed in the class of manmade objects. What is more, a living organism lacking the power of locomotion is called as plant (Miller, 1998), which is a type of natural objects. The definition of the building is that a structure that has a roof and walls and stands more or less permanently in one place (Miller, 1998).

The building is also a kind of structure or construction. Thus, the module of source of objects can divide concepts into some small subsystems, such as structure, transportation, and plant (Figure 5-4).

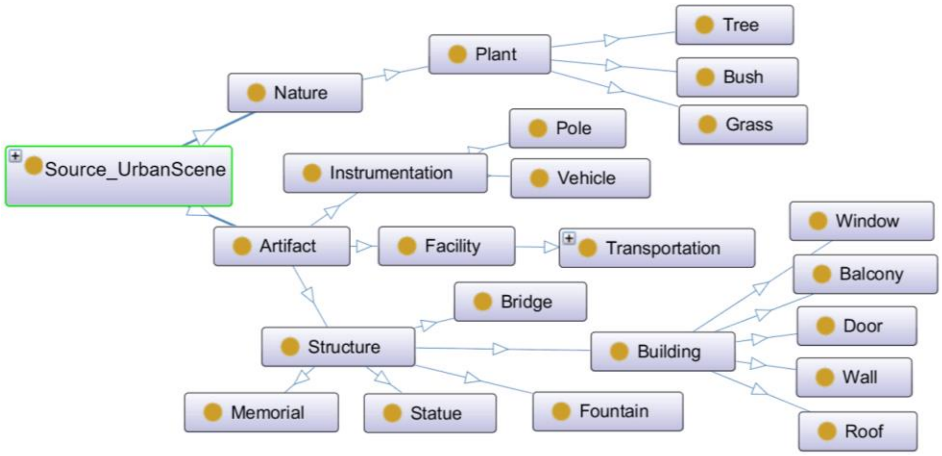


Figure 5-4 Classification of concepts according to their source or nature.

5.5.3.4 Geometry Module

Geometry is a branch of mathematics. Geometric information can be used to describe the spatial properties of objects such as length, area, and volume, etc. Additionally, they determine the relative position of geometric shapes in the defined space. For example, the spatial relations can be inferred from existing geometry theorems. The geometric models offer fundamental geometric information to represent objects. For example, a building with simple shape can be modeled as a cube and a common wall is represented as a planar rectangle with its boundary points. Therefore, a geometric module is essential to an ontology to accomplish the task of extracting semantic features of objects from point clouds.

Geometric shapes can be divided into 0D, 1D, 2D and 3D geometric shapes. In 2D space, shapes are decided by their boundaries. In contrast, in 3D space, geometric shapes are not only determined by their boundaries, but also the types of geometry where they locate. Those shapes located in a plane in 3D space are defined by the parameters of the plane equation in 3D space and their boundaries. Those complex 3D geometries such as a polyhedron comprised of several planes can derive from basic planar geometries. Other geometries, such as spheres, cylinders and cones also need the parameters of equations and their boundaries to be defined. Finally, the concepts of geometries in 3D space are classified by their geometric properties following the geometry classes of ISO 19107 (Kresse, 2004) (Figure 5-5).

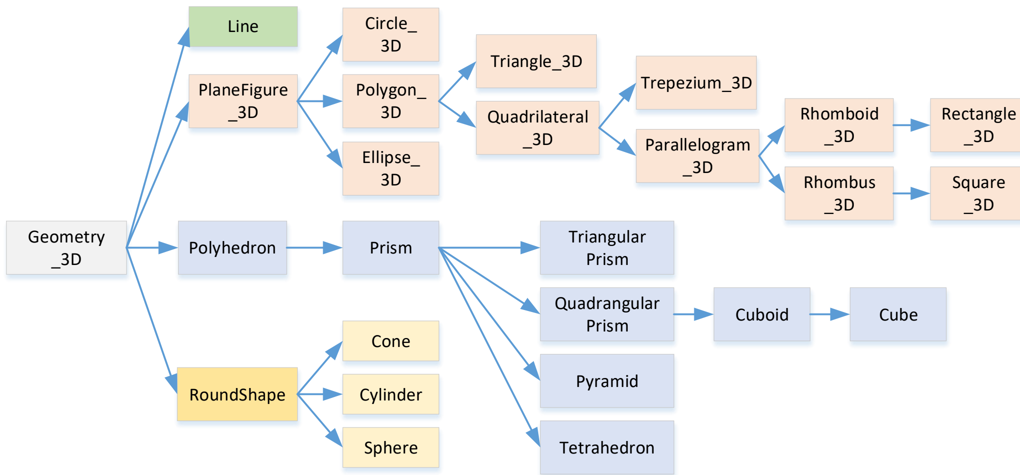


Figure 5-5 Classification of concepts related to geometry in 3D space.

5.5.3.5 Composition Module

The composition indicates the concepts of the aggregation of objects. Three levels of composition relationship for objects are: (1) aggregation of the whole object by its components; (2) a subsystem combined with some objects; (3) a system comprised of several subsystems.

- Components aggregation: an individual object can be broken down into some components that cannot be decomposed into any small parts. For example, in a geometric model of a building, the patch representing a wall may not be divided into smaller pieces.
- Subsystem aggregation: this relationship indicates the abstract concepts for representing functionally relevant sets. For example, a parking lot area comprises a piece of ground with some vehicles, some sign poles and some poles for paying the parking fee.
- System aggregation: this level is used to represent the top-level aggregation relationships between objects in an independent scene or objects in a network. Examples include transportation system containing many parts severing for transportation.
- In this module, the concepts in upper-level represent generic object models with the relation of function-related aggregation. The lower-level aggregation forms the composition of the components of a single object.

5.5.3.6 Spatial Relations Module

Spatial relations involves topological, metric and directional relations, which are all capable of describing a scene with some semantic information (Mark, 1994). Topological relations describe the relative relation of an object in the space with respect to other objects. This qualitative information plays a significant role in spatial analysis because it is independent of the coordinate system definition and transformations such as translation, rotation, and scaling (Egenhofer, 1990b). In the following, the spatial relations in 2D and 3D spaces are described based on the concept of "region". Based on the topological relations of planar regions in 3D space, the formalized representation of spatial relations in 3D space can be derived from point clouds with geometric information and semantic description.

To define topological relationships in a 2D space, we can use the relations between "regions" for demonstration purpose. A region is defined as a 2-cell object with a non-empty, connected interior in 2D space (Egenhofer, 1990a). The region is applied to represent all kinds of 2D spatial objects because regions are the principal bearers of spatial properties and relations (Roeper, 1997). Thus, topological relations between spatial objects come from Region Connection Calculi (RCC-8) (Egenhofer, 1989; Randell, 1992). In the "4-Intersection" model (4IM) (Egenhofer, 1989) and the "9-Intersection" model (9IM) (Clementini, 1994; Egenhofer, 1990b; Mark, 1994), eight possible topological relations between regions are defined as disjoint, meet, overlap, cover, coveredBy, contain, containedBy and equal (Egenhofer, 1991a).

Topological relations between 3D spatial objects depend on the way objects are modeled. Constructive Solid Geometry (CSG) and Boundary Representation (B-Rep) are among models to represent spatial objects in 3D space. Thus, the topological relations between 3D spatial objects are classified into two categories: topological relations between 3D solid objects, and topological relations between 3D objects with internal space. The easily recognizable eight possible relations of 3D objects with inner space are Disjoint, Meet, Overlap, Equal, Contain, ContainedBy, Cover, CoveredBy (Zlatanova, 2004). However, the topological relations for 3D solid objects are only Disjoint and Meet relations. For determining the topological relations among 3D objects, RCC-3D (Albath, 2010b) was designed for the spatial reasoning on 3D spatial objects based on the RCC-8 model. RCC-3D defines 13 relationships, but the discrimination of some relations requires particular projection in the view of a reference plane (Sabharwal, 2011). The RCC-3D relations can be used to describe the occlusion between objects. However, it cannot be used to present topological relationships between components of an object to form a whole 3D model. In 3D B-Rep models, complex objects are composed of some components represented by geometric primitives with diverse properties, such as geometric shapes, size, and their topological relations (Freeman, 1975). For connecting these components to form a whole 3D model and extracting their semantic features based on components and their topological relations, the formalized representation of topological relations between components of objects is required.

For the topological relations of B-Rep objects and CSG objects, we can use the existing topological relations (Zlatanova, 2004) in the ontology. The topological relations between object components need to be developed further in this ontology. The topological relations among object components are defined based on the concept "Planar Region". A planar region in 3D space is defined as a planar area with non-empty, connected interior, which is fundamental to represent topological relations between objects components. In 3D space, the topological relations among the planar region are firstly decided by the spatial relations of two planes that contain planar regions. We can distinguish three cases:

- If the planes are parallel, these two planar regions are disjoint.
- If the planes are coplanar, the relation between two planar regions is determined as in 2D space.
- If the planes are intersecting, two planar regions can have many possible topological relations.

Therefore, the topological relations are classified into three classes: topological relations of B-Rep objects, topological relations of CSG objects and topological relations of planar regions in 3D space. In the class of topological relations between planar regions, there are three cases: planar regions on coplanar planes, parallel planes and intersecting planes (as shown in Figure 5-7). For each case, there could be several examples as described in (Xing, 2016b).

Based on the above category of topological relation in 3D space, the topological relations need to be represented by a formalized representation to distinguish them. The topological relations in the intersecting case of two plane equations are disjoint, meet and intersect. The relation "Disjoint" is defined as there is no common part between two planar regions. The relation "Meet" indicates that there are common parts only located on the boundaries of the planar regions. The relation "Intersect" is the evolution of "Overlap" from RCC-8. There are also several cases of these three topological relations in 3D space. In the following, a formal representation of topological relations between two planar regions representing the components of more complex objects is developed. Based on the 4IM and 9IM topological relations definition, the topological relations among planar regions can be represented by a matrix consisting of boundaries, interiors and the intersection line of two plane equations. The definition of DE-9IM for planar regions (Xing, 2016b) is shown as follows:

$$T_p(A,B) = \begin{bmatrix} \dim(A^\circ \cap B^\circ) & \dim(A^\circ \cap \partial B) & \dim(A^\circ \cap Il) \\ \dim(\partial A \cap B^\circ) & \dim(\partial A \cap \partial B) & \dim(\partial A \cap Il) \\ \dim(Il \cap B^\circ) & \dim(Il \cap \partial B) & \zeta \end{bmatrix} \quad \textbf{(Eq 5-1)}$$

where

A° = indicates the interior of the region *A*;

∂A = the boundary of the region *A*;

B° = the interior of the region *B*;

∂B = the boundary of the region *B*;

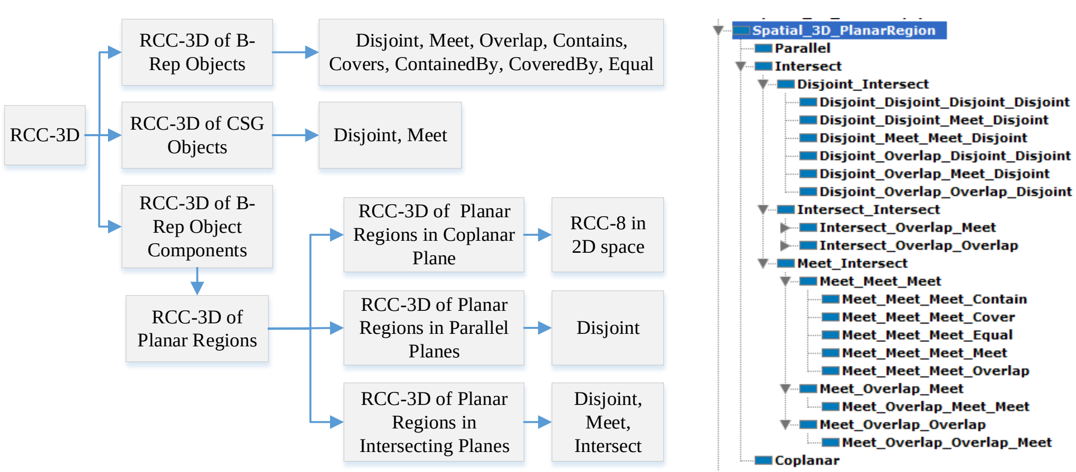
Il = intersection of two planes containing planar regions *A* and *B*;

ζ records the topological relations of the primitives comprised of the common parts between the planar region *A* and *B* and intersection line. The primitives are all located on the intersection line;

dim() = dimension operator.

Based on DE-9IM for planar regions, the details of topological relations between planar regions are decomposed into three parts (Figure 5-6):

1) The relation between the planar region *A* and the intersection line *Il*, including Disjoint, Meet and Overlap;
2) The relation between the planar region *B* and the intersection line *Il*;
3) The relations between primitives on the intersection line IL that are the common part comprised of planar region *A* and the intersection line and the common part comprised of planar region *B* and the intersection line.



(A) (B)

Figure 5-6 Classification of topological relations in 3D space (A) and their formalized representation in the ontology (B).

For the topological relations between a planar region and an intersection line, the possible relations are Disjoint, Meet and Overlap. The possible primitives on the intersection line comprised of the common parts of the planar region and the intersection line are points (for Meet relation between a planar region and the intersection line) and line segments (for an Overlap and a Meet relations between a planar region and the intersection line) (Table 5-2). The possible topological relations constitute point-point, point-line segment and line segment-line segment relations (Xing, 2016b). Finally, the formal representation of topological relations between planar regions is composed of four parts: (1) the overall topological relation of two planar regions; (2) the relation between planar region *A* and the intersection line; (3) the relation between planar region *B* and the intersection line; and (4) the topological relations of primitives on the intersection line. Some examples of topological relations in the case of Disjoint, Meet and Intersect under the "RCC-3D planar regions in Intersecting planes" can be found in (Xing, 2016b).

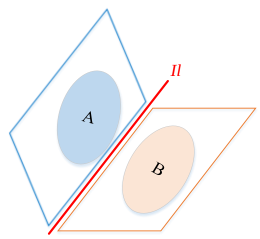
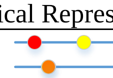
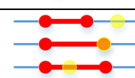
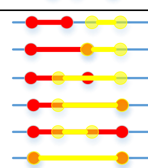


Figure 5-7 Illustration of an example of a topological relation between two planar regions (*A* and *B*) in 3D space.

Table 5-2 Basic topological relations between primitives on the intersection line (Xing, 2016b).

Type of Relations	Graphical Representation	Topological Relations
Point-point relations		Disjoint, Equal
Line segment-point relations		Disjoint, Meet, Contain
Line segment-line segment relations		Disjoint, Meet, Overlap, Cover, Contain, Equal

In conclusion, the topological relations in 3D space are defined and formalized according to the way of representing 3D spatial objects. The category includes the topological relations of B-Rep objects and CSG objects, and the topological relations between planar regions representing the components of B-Rep objects. In the automatic 3D modeling of point clouds, the B-Rep models are employed to represent 3D objects and their components. Therefore, the topological relations between objects and that among the components of an object are all represented and discriminated by the formalized semantic representation of topological relations. Finally, based on these types of topological relations, the module of spatial relations in the ontology is created to represent the possible topological relations.

5.5.4 Objects Attributes

Attributes describe the features of objects, including original features such as the dimension of geometries (length, width, height, area and coordinate, etc.) and assign semantic information such as the label names of objects, the functions of objects. Attributes are important to describe objects. The attributes can be classified from the views of attribute types and attribute modalities referring to classification in (El-Diraby, 2011). The attributes are classified into six types in the ontology (Table 5-3).

5.5.5 Constraints

Constraints limit the properties of an object to differentiate it from other objects. The purpose of constraints is to complete the specific tasks in aid of common sense knowledge and unique features in a certain case. The constraints can describe the knowledge of objects. The constraints are formalized as inferential and computer understandable first-logical-based rules. In summary, constraints are given from different aspects for the recognition of objects.

- Geometric dimensional constraints: for feature recognition, the essential and intrinsic attributes of objects, including measurable attributes, geometry shape attributes, limit the rough classification of objects.
- Spatial relations constraints: spatial constraints link objects in a local part of the urban scene. For some objects belonging to the transportation system, cars are moving on the road surface. Sidewalks are extending following the road or connected to roads. Traffic signs poles or light poles located near to the roads or sidewalks. Especially for man-made objects, components of objects have some topological relations constraints in the aspect of design or functional requirements. These constraints can also be represented as rules in the knowledge base.
- Logical constraints: some constraints are given not for the measurable or spatial constraints but from the view of logic. An example for interpreting logical constraints is that a parking lot is a piece of ground where accommodates a large amount of orderly arranged vehicles. Because logical constraints could associate concepts according to their logical relations of functions, locations, and system relevance, they are defined in the level of relevance among components of objects. Similarly, they can be defined in the level of subsystem consisting of objects.

Table 5-3 Classification of attributes in the ontology

Attribute Types	Explanation	Examples
Dimensional attributes	measurable quantitative dimension of objects	size, height, length, width, area
Geometric shape attributes	describe geometric shapes	normal, boundary, surface type (plane, curved), shape(rectangle, square, circle)
Spatial attributes	location-related attributes and spatial relations	X-coordinate, Y-coordinate, Z-coordinate, latitude, longitude
Function attributes	object functions in a system or the roles of objects in a scene	lighting (for light pole), control traffic (for traffic sign), passing (for door)
Dependency attributes	attributes representing the interdependency between components or objects	logical dependency, geographic dependency, location dependency
System (combination) attributes	attributes are the terms for a group of objects or a subsystem.	roof styles (such as gable, hip, shed, flat, and mansard and so on), traffic system, intersection.

5.5.6 Relationships Definition

Relationships build the association among concepts. Relationships are of importance in the design of ontology due to their enriched definition and description of linking concepts. For the purpose of easy comprehension of relationships, they can be classified by their meaning.

Hyponymy: it is the “is-a” relationship. It is the semantic relation of being subordinate or belonging to a lower rank or class (Miller, 1998). Relationships including the definition of the kinds of concept constitute the backbone of ontological taxonomy tree structure. “is-a” relationship also contains some converted relationships, including synonymy and antonymy relations. “isEquivalentTo” and “isSimiliarTo” belong to synonymy relations. At the same time, “isDisjoint” and “isOpposite” are main relationships of antonymy (El-Diraby, 2011).

Meronymy: it is the “whole-part” relationship. It indicates the relationship of grouping concepts as a whole or decomposing concepts into parts. The relationships of “isPartof” and “isComposedof” are commonly defined in whole-part relations between concepts. In OWL ontologies, there are listed use cases of whole-part relations, such as defining “whole-part” relationships for individuals and class definition. Although the relationship “subclassOf” and “kind of” all are used to organize concepts hierarchically, their distinction must be made to decide the relationship in hierarchical concepts (Natasha, 2005), including descriptive relations, possessive attributes (“has” relation), spatial relationship (locateAt, connect, align, parallel, vertical, direction, above, on, in), function relationship (hasFunction), and composition relations (must-beComposedOf, could-beComposedOf).

In summary, the relationships between concepts in the ontology need to be mapped into the relationship categories as mentioned above. In OWL ontology, “is-a” relationship is mapped as “subClassOf”. “whole-part” relationship is described in detail in accordance with the various cases (Natasha, 2005). Based on these relationships for building an ontology, some descriptive relationships are easily set among concepts. Inexplicit and indefinite relationships can also be identified and defined by property restrictions.

5.5.7 Axioms

The spatial and geometric relations are necessary for describing relationships between geometric primitives and obtaining accurate boundaries among primitives by interactions among geometries. Moreover, geometric relations can be obtained by reasoning using theorems on solid geometry. For example, if there are no common parts between two planes, then these two planes are parallel, or if two planes are all perpendicular to the same line, they are parallel as well. The theorems are easily predefined in ontologies as semantic rules. As a result, the spatial relations between geometric primitives are not only directly computed from geometric properties, but also from the reasoning on theorems, especially those describing complex geometric relationships.

```
Plane(?P1), Plane(?P2), Line(?L1), isPerpendicularTo(?P1,?L1), isPerpendicularTo(?P2,?L1) ->
isParallel(?P1,?P2)
```

More constraints are needed for complex geometric theorems in 3D space. For example, in 2D space, if two lines are orthogonal to the same line, these two lines are parallel. The semantic rules are defined as follows:

```
Line(?L1), Line(?L2), Line(?L3), isPerpendicularTo(?L1,?L3), isPerpendicularTo(?L2,?L3) ->
isParellel(?L1,?L2)
```

However, the above rule cannot hold if we replace the lines as planes for reasoning the parallel relationship between planes in 3D space. More constraints are required to reason spatial relation of planes. The following rule is designed for reasoning the parallel relationship between planes in 3D space.

```
Plane(?P1), Plane(?P2), Plane(?P3), Plane(?P4), isPerpendicularTo(?P1,?P3), isPerpendicularTo(?P1,?P4),
isPerpendicularTo (?P3,?P4), isPerpendicularTo(?P2,?P3), isPerpendicularTo (?P2,?P4) ->
isParallel(P1,?P2)
```

In conclusion, geometric relation axioms can be predefined as semantic rules for reasoning on the geometric relations between objects in 3D space. Based on these rules, new spatial relationships could be reasoned from the known fundamental relations among primitive geometric objects.

5.6 Experimentation and Results

The primary challenge for evaluation of an ontology is the terminology validation. The terms associate ontology with universal knowledge. Even in philosophical ontologies, the definition of terms is a complex task. However, for our application ontology, the definitions of generic terms are not the primary requirement as the existing knowledge in the application domain is used in the ontology building process. Additionally, universality is not the objective either. In general, it is difficult to achieve the consensus knowledge representation because the ontology is subjective by its nature (El-Diraby, 2011). For upper ontology, the definitions of terms and the determination of universal concepts could not be accepted in a short time. Consequently, the development of widely accepted ontology needs to be criticized and updated by researchers after their use over many years.

For evaluating an application ontology, some requirements of measures need to be established during the definition of the expectation of this ontology and finally to evaluate the corresponding achievements in the use. For application ontology aiming at object recognition in a point cloud of an urban scene, some competency questions are used to test its validity and its capacity to answer those questions. The competency questions are more specifically, including the recognition of geometry composed of planar segments and the recognition of building roof shapes from segmentation results of point clouds.

5.6.1 Consistency Check in Protégé

The ontology was built and represented by OWL in Protégé. In this software, concepts are represented as classes, and instances are described as individuals. Concepts, individuals and properties are defined using Description Logics (DLs). Additionally, several reasoners, such as Pellet, FACT++, Racer, can perform reasoning on concepts and semantic rules. Protégé can also help to evaluate the overall consistency of an ontology. Pellet reasoner provides functions for checking the consistency of ontologies, explaining inferences for reasoning results, and answering SPARQL queries (Sirin, 2007).

5.6.2 Reasoning Experiments Based on Knowledge Base

As mentioned previously our ontology is designed and implemented in Protégé and Pellet is used as the reasoner on the knowledge base. The ontology is stored as owl files. Moreover, OWL API is a Java API for the operations of ontology, such as creating, manipulating and serializing OWL ontologies. Moreover, it provides OWLReasoner interface to access to the functionality of reasoning, such as consistency checking, computation of class and property and entailment of axioms (Horridge, 2011). More importantly, it is feasible to define semantic rules in Protégé. Then semantic rules can be used to reason knowledge in reasoner Pellet. In summary, automated reasoning based on predefined ontologies and semantic rules proves the feasibility of knowledge reasoning.

5.6.2.1 Experiment of Recognizing a Cuboid from Planar Regions

The first experiment shows a simple example for the extraction of an object from a point cloud. In this experiment, we show that if several planar regions are extracted from point clouds, the proposed ontology and rules are capable of recognizing a cuboid based on the geometric information extracted from the point cloud. For this purpose, we need the formation on plane-based prism and the topological relations among its components to recognize prism. For instance, for a cuboid, six planar regions can be segmented by geometric detection algorithms from point clouds. Their topological relations can be identified from the quantitative geometric information of planar segments using the proposed formalized topological relations. Each planar region will be added into "PlanarRegion" class as instances. In Figure 5-8, planar region *Pr1* and *Pr4* are opposite. Likewise, *Pr2* and *Pr5*, *Pr3* and *Pr6* are opposite as well. For manifold geometry, each edge is shared by two adjacent facets in a closed prism. According to the definition of recognizing cuboid formalized by semantic rules, the conclusion will be reasoned based on the known properties of instances in "PlanarRegion" class.

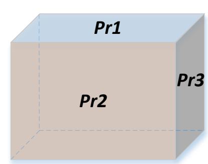


Figure 5-8 A simple cuboid example consisting of six planar regions.

To recognize prisms from a set of planar regions, the topological relations among regions are very important. A simple subset of concepts is extracted from the ontology in the knowledge base to reason on the cuboid with the help of topological relations among the planar regions and their boundary (Figure 5-9). In this figure, "PlanarRegion" class defines the concept of planar regions. "Cuboid" and "FacetofCuboid" classes are linked by the object property "isPartOf". A cuboid concept is composed of several parts that are planar regions with special constraints and relations in 3D space. Thus, the instances of "PlanarRegion" class, such as *Pr1*, *Pr2*, *Pr3*, *Pr4*, *Pr5*, *Pr6*, are defined in the set "A" which is an instance of "Set" class. Moreover, the relations between the instances of "PlanarRegion" class are described, for example, all properties of *Pr1* are shown in Figure 5-10. Similarly, the properties of other instances are defined as well.

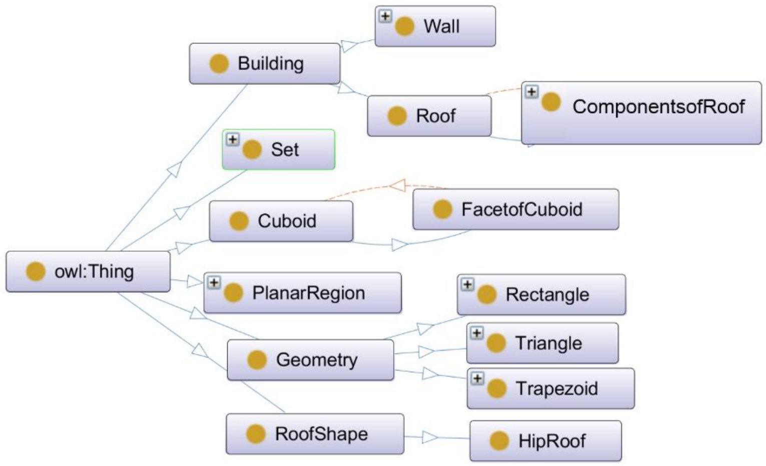


Figure 5-9 A subset of concepts for the recognition of a cuboid from planar regions.

Pr1	*isInset* ***A*** *isNeighboringTo* ***Pr2*** *isNeighboringTo* ***Pr3*** *isNeighboringTo* ***Pr5*** *isNeighboringTo* ***Pr6*** *isMeet_Equal_Vertical* ***Pr2*** *isMeet_Equal_Vertical* ***Pr3*** *isMeet_Equal_Vertical* ***Pr5*** *isMeet_Equal_Vertical* ***Pr6***

Figure 5-10 The relations and properties of the instance *Pr1*.

Based on these concepts and topological relations, semantic rules are defined for reasoning on the knowledge related to the specific object defined above. In the following rules, the relation “isMeet_Meet_Meet_Equal” is obtained from basic geometric information of planar regions following the definition of DE-9IM for planar regions and detailed steps presented in (Xing, 2016b). It indicates detailed formalized representation of predefined topological relations of the two planar regions in the spatial relations module. “Vertical” indicates another spatial relation between two planes *Pr1* and *Pr2*. In the definition of rules, “isInSet (?x, ?A)” indicates that an individual x is in the set A. Based on the above definitions, the following semantic rules are used to reason on the knowledge for the extraction of a cuboid from planar regions, their properties and their relations.

PlanarRegion(?Pr1), PlanarRegion(?Pr2), isNeighboringTo(?Pr1,?Pr2),
isMeet_Meet_Meet_Equal(?Pr1,?Pr2), isVerticalTo(?Pr1,?Pr2) -> (1)
isMeet_Equal_Vertical(?Pr1,?Pr2)

The rule (1) is designed to test if the topological relation between two planar regions is "Meet_Meet_Meet_Equal" and their spatial relation is vertical to each other.

PlanarRegion(?Pr1), PlanarRegion(?Pr2), PlanarRegion(?Pr3), PlanarRegion(?Pr4),
PlanarRegion(?Pr6), Rectangle(?Pr1), isNeighboringTo(?Pr2,?Pr1), isNeighboringTo(?Pr2,?Pr3),
isNeighboringTo(?Pr2,?Pr4), isNeighboringTo(?Pr2,?Pr5), isMeet_Equal_Vertical(?Pr2,?Pr1), (2)
isMeet_Equal_Vertical(?Pr2,?Pr3), isMeet_Equal_Vertical(?Pr2,?Pr4),
isMeet_Equal_Vertical(?Pr2,?Pr6) -> FacetofCuboid(?Pr2)

The rule (2) is defined to determine if a planar region belongs to a cuboid using the topological relations between it and all its neighbors.

Set(?A), PlanarRegion(?Pr1), PlanarRegion(?Pr2), PlanarRegion(?Pr3), PlanarRegion(?Pr4),
PlanarRegion(?Pr5), PlanarRegion(?Pr6), isInSet(?Pr1,?A), isInSet(?Pr2,?A), isInSet(?Pr3,?A),
isInSet(?Pr4,?A), isInSet(?Pr5,?A), isInSet(?Pr6,?A), FacetofCuboid(?Pr1), FacetofCuboid(?Pr2), (3)
FacetofCuboid(?Pr3), FacetofCuboid(?Pr4), FacetofCuboid(?Pr5), FacetofCuboid(?Pr6) ->
Cuboid(?A)

5.6.2.2 Axioms and Rules to Formally Define a Hip Roof from Planar Regions

The second experiment is used to recognize a hip roof style from a set of planar regions. The styles of roofs vary from regions to another region. Most common architectural roof styles can be identified and defined in the knowledge base. Here we choose the hip style as an example. A hip roof is defined as a type of roof where all sides slope downwards to the walls with a gentle slope (Curl, 2006). All sides come together to form a ridge at the top of the roof. A typical hip roof is shown in Figure 11. In the hip style, there are two triangles and two trapezoids consisting of hip roof. They are individuals in the class "PlanarRegion" and they belong to "ComponentsofRoof". According to the elevation information of planar regions and their relations with a wall, they can be defined as the components of a roof. The "ComponentsofRoof" class represents the concept that defines parts of the roof structure. The object property "isSloptTo" is defined to describe the slope of planar regions. It can be determined by computing the dihedral angle between two planes. For example, if the roof part *Pra1* is sloping to wall W1, the dihedral angle of them will be over 90 degrees. The individual *Pra1* represents the triangle 1 in Figure 5-11. Additionally, the "Tri" is an instance of the class "Triangle" which is a subclass of "Geometry" class. The properties and relations of the *Pra1* are presented in Figure 5-12. Other parts of the hip roof can be defined similarly by their properties and their respective relations. These properties and relations are then used to define semantic rules for the subsequent reasoning process.

The following rule is used to reason on the provided knowledge for extraction of the hip roof.

Set(?B), Wall(?W1), Wall(?W2), Wall(?W3), Wall(?W4), Trapezoid(?Trap), Triangle(?Tri), PlanarRegion(?Pra1), isInSet(?Pra1,?B), ComponentsofRoof(?Pra1),PlanarRegion(?Pra2), isInSet(?Pra2,?B), ComponentsofRoof(?Pra2),PlanarRegion(?Pra3), isInSet(?Pra3,?B), ComponentsofRoof(?Pra3),PlanarRegion(?Pra4), isInSet(?Pra4,?B), ComponentsofRoof(?Pra4),hasShape(?Pra1,?Tri), hasShape(?Pra2,?Trap), hasShape(?Pra3,?Tri), hasShape(?Pra4,?Trap), isMeet_Meet_Meet_Equal(?Pra1,?Pra4), isMeet_Meet_Meet_Equal(?Pra1,?Pra2), isMeet_Meet_Meet_Equal(?Pra3,?Pra4), isMeet_Meet_Meet_Equal(?Pra3,?Pra2), isMeet_Meet_Meet_Equal(?Pra2,?Pra3), isMeet_Meet_Meet_Equal(?Pra2,?Pra1), isMeet_Meet_Meet_Equal(?Pra2,?Pra4), isMeet_Meet_Meet_Equal(?Pra4,?Pra3), isMeet_Meet_Meet_Equal(?Pra4,?Pra1), isMeet_Meet_Meet_Equal(?Pra4,?Pra2), isSlopeTo(?Pra1,?W1), isSlopeTo(?Pra2,?W2), isSlopeTo(?Pra3,?W3), isSlopeTo(?Pra4,?W4) -> HipRoof(?B) (4)

In the rule (4), all the roof components, such as *Pra1*, *Pra2*, *Pra3*, and *Pra4*, are the instances of the concept "PlanarRegion" and they are in the set B. In this set, if all the instances meet the defined constraints of geometric shapes and the topological relations among them in the rule, a hip roof can be reasoned from a set of planar regions.

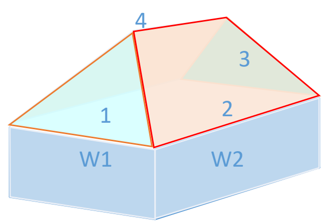


Figure 5-11 A building model with hip roof structure (the numbers 1 to 4 represent the individuals *Pra1*, *Pra2*, *Pra3* and *Pra4*. W1 and W2 are the individuals of class "Wall").

Pra1	*isInSet* ***B*** *isMeet_Meet_Meet_Equal* ***Pra4*** *isMeet_Meet_Meet_Equal* ***Pra2*** *hasShape* ***Tri*** *isSlopeTo* ***W1***

Figure 5-12 The properties and relations of instance *Pra1*.

5.6.2.3 Experiment for Recognizing a Hip Roof from Point Clouds

The third experiment presents the case of reasoning the higher levels of knowledge about building roof styles from point clouds based on our proposed knowledge base. After the segmentation of point clouds, a cluster of point clouds is segmented into seven planar segments (Figure 5-13(A)). The boundaries of these planar segments can be extracted from segmentation results as shown in Figure 5-13(B). When having the boundaries of planar segments, the topological relations between planar segments are obtained. We employ the method of extracting topological relations between planar regions (Xing, 2016b) to express the topological relations of two planar segments. The average distance between each boundary point and its *k* nearest neighbors are used to decide whether this boundary point should be projected onto the intersection line. If the distance between this boundary point and the intersection line is less than the calculated average distance with its *k* nearest neighbors, this boundary point is projected onto the intersection line (Figure 5-13(C)). The points projected on the intersection line form the primitives (point or line segment). The topological relations between primitives on the intersection line are important to determine the topological relations of planar regions. For example, the boundary points of two trapezoid planar segments are projected on the intersection line to form the ridge of the roof (Figure 5-13(D)). Here, we introduce several parameters as prior knowledge to the knowledge base that will help us in the computation of relations between planar regions. For instance, we choose 2 times of the average distance between points and their *k*-nearest neighbors (k = 6) as the threshold value to detect the points on the intersection line. We use this value to decide if the boundary points should be projected onto the intersection line and to determine the relations of the endpoints of line segments. As shown in Figure 5-13(E), the distances between the endpoints of two line segments are 0.089 m and 0.53 m, which are smaller than the calculated thresholds. Thus, the topological relations between two planar regions with trapezoid shape are “Meet-Meet-Meet-Equal” after the comparison of endpoints of two line segments. Similarly, the topological relations of other planar segments can also be obtained from point clouds.

Based on the segmented planar segments and their dimension properties measured from the extracted planar regions, their spatial properties, and their topological relations, the planar segments are expressed as facts and as the instances of concepts defining a roof structure in the knowledge base. Then semantic rules as defined previously can be used to reason on this knowledge base. Because Airborne LiDAR scanners observe building roofs on the top, vertical structure of buildings are less present in the point clouds. We define rules to recognize roof shapes from Airborne LiDAR point clouds without the help of walls. For example, we define that the components of the hip roof have a slope to the ground to replace the properties defined with respect to the walls. The following rules are defined to reason the building roof styles from the segmentation results of point clouds.

Set(?B), Ground(?g), Trapezoid(?Trap), Triangle(?Tri),PlanarRegion(?Pra1), isInSet(?Pra1,?B), ComponentsofRoof(?Pra1),PlanarRegion(?Pra2), isInSet(?Pra2,?B), ComponentsofRoof(?Pra2),PlanarRegion(?Pra3), isInSet(?Pra3,?B), ComponentsofRoof(?Pra3),PlanarRegion(?Pra4), isInSet(?Pra4,?B), ComponentsofRoof(?Pra4),hasShape(?Pra1,?Tri), hasShape(?Pra2,?Trap), hasShape(?Pra3,?Tri), hasShape(?Pra4,?Trap), isMeet_Meet_Meet_Equal(?Pra1,?Pra4), isMeet_Meet_Meet_Equal(?Pra1,?Pra2), isMeet_Meet_Meet_Equal(?Pra3,?Pra4), isMeet_Meet_Meet_Equal(?Pra3,?Pra2), isMeet_Meet_Meet_Equal(?Pra2,?Pra3), isMeet_Meet_Meet_Equal(?Pra2,?Pra1), isMeet_Meet_Meet_Equal(?Pra2,?Pra4), isMeet_Meet_Meet_Equal(?Pra4,?Pra3), isMeet_Meet_Meet_Equal(?Pra4,?Pra1), isMeet_Meet_Meet_Equal(?Pra4,?Pra2), isSlopeTo(?Pra1,?g), isSlopeTo(?Pra2,?g), isSlopeTo(?Pra3,?g), isSlopeTo(?Pra4,?g) -> HipRoof(?B) (5)

In these experiments, first, we have tested the competency of recognized complex geometries such as a cuboid from planar regions. Then we have used the geometric properties and topological relations of planar regions representing the components of roof structures to recognize the types of roof shape. Finally, we have tested the capability of recognizing roof shapes from point clouds using the proposed knowledge base. The experiments showed that our proposed knowledge base represents and describes the knowledge of higher-level semantic features of objects. The automatic extraction of semantic features is achieved based on the knowledge of properties and relations of objects obtained from segmentation results as well as based on the knowledge in an urban scene.

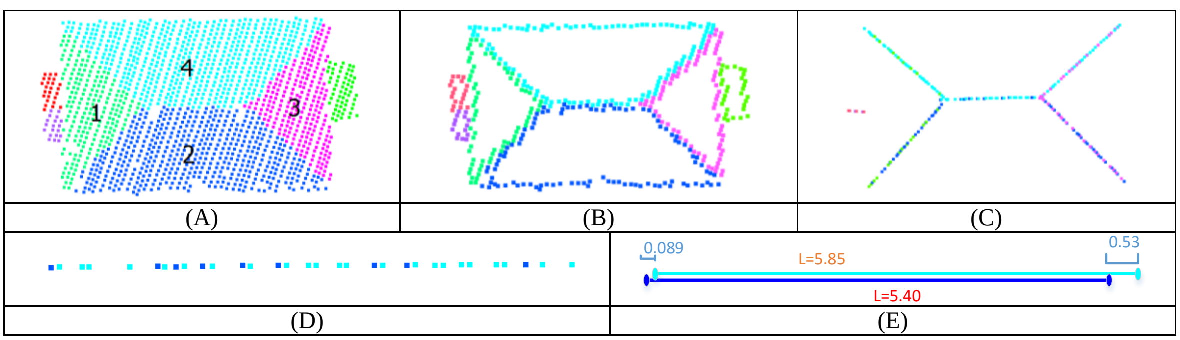


Figure 5-13 (A) Segmentation results; (B) boundaries and (C–E) the process of the determination of topological relations between components extracted from a point cloud.

In some cases, missing parts in point clouds can affect the correctness of feature recognition. However, depending on the presence of the missing parts in the data, our approach can go farther in the recognition of objects compared to more standard geometric algorithms. For instance, in the last experiment, if the missing parts do not impact the determination of geometric shapes and topological relations of the objects components, such as the missing parts locate in the interior and boundaries of a planar segment (as shown in Figure 5-14(A,B)), semantic features of building roof shape still can be obtained by the reasoning process on the available knowledge. However, if the missing parts limit significantly the available information on the object (Figure 5-14(C,D)), the reasoning results from the knowledge base would be uncertain or incomplete.

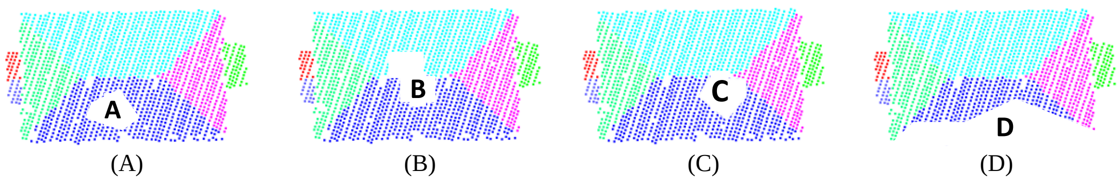


Figure 5-14 Impacts of missing data on feature recognition. (A) The missing part located in the interior of a planar segment has no impacts; (B) The missing parts of the interior and boundary do not impact feature recognition; (C) The missing parts of the interior and boundary impacts the identification of topological relations; (D) A large area of missing part has impacts on the determination of geometric shapes and topological relations.

5.6.2.4 Experiment for Recognizing Semantic Features of Buildings from Point Clouds

In this experiment, we conduct an experiment on a part of building selected from a mobile LiDAR point cloud. First, we use a clustering algorithm to find clusters corresponding to buildings in the point cloud (Figure 5-15(A)). Second, the region growing algorithm is chosen to segment the cluster into planar segments based on robust normal estimation (Nurunnabi, 2015) which allows estimating surface normal from a point cloud with noise (Figure 5-15(B)). Following a region growing process, RANSAC algorithm is used to detect different planes in the building structure (Figure 5-15(C)).

Now we need to recognize different components of the building. For this purpose, we make use of the proposed knowledge base that describes different components of a building. For instance, a wall is defined as any opaque part of the external envelope of a building that makes an angle of 70° or more with respect to the ground (Ltd, 2017). A roof is considered to be locally the uppermost part of a building with a set of specific properties that allows distinguishing it from a wall. We use this knowledge to recognize a possible roof or wall structures extracted following from a point cloud. Figure 5-15(D) shows a part of the building that represents a potential roof structure as the planar segments, in this case, have an angle less than 70° with respect to the ground. In contrast, Figure 5-15(E) presents other set of planar segments that correspond to the above semantic definition a wall.

Based on the previous steps, we can preliminarily extract the roofs and walls of the building. In addition to the building parts, there are some other small planes detected in the point cloud. These planar segments belong to a tree close to the building as shown in Figure 5-15(D, E). The detailed knowledge about the building extracted from the point cloud is represented as facts in the knowledge base and specific rules are defined to help identify walls and roofs.

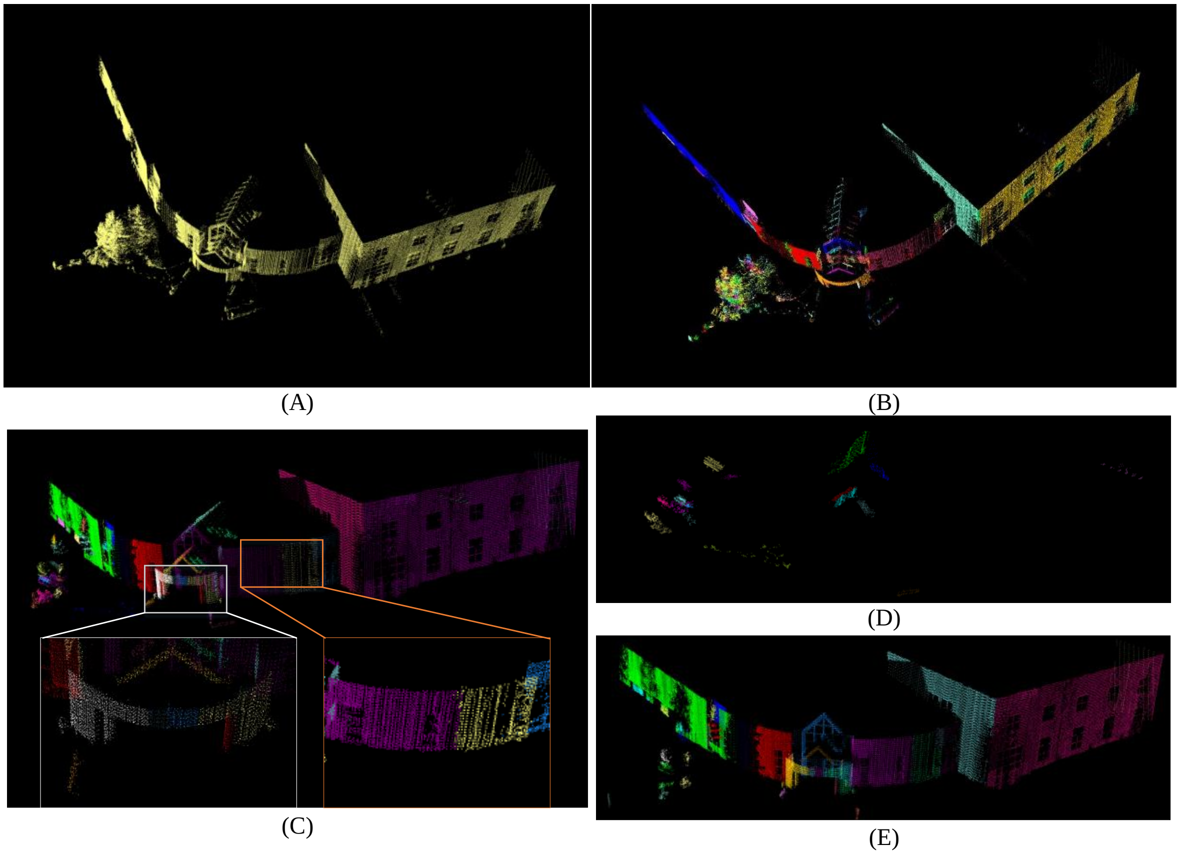


Figure 5-15 Recognition of semantic features of the components of a building from point cloud. (A) A cluster; (B) planar segments after region growing processing; (C) planes detected by RANSAC algorithm using plane models; (D) a potential roof structure; (E) a potential wall structure.

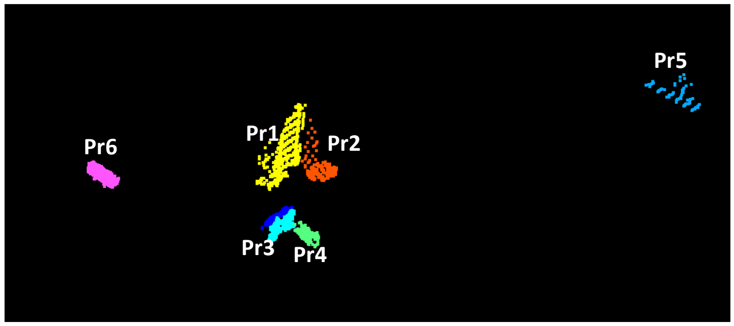
Some rules are defined to recognize a wall and a roof and its shape following a reasoning process (Table 5-4). For recognizing a wall, we consider not only the constraints between planes and ground, but also the spatial relations among the planar segments that can be coplanar. The walls of the building are presented in Figure 5-16(B). For a roof, the spatial relations between planes and ground, the areas of planes and the height information are considered. In addition, among the planar segments, there may be some that will not be recognized based on their own properties. In this case, these planes are analyzed within their spatial contexts. For instance, a small segment of a roof that is not recognized by its own, would be analyzed in its context. Thus, its semantic features will be obtained following the reasoning process with respect to the presence of other parts of the roof that are already recognized.

Based on these rules, the reasoning process allows the extraction of semantic features of building components. As we explained earlier, planar segments in point clouds are instances of concepts in the knowledge base. This implies that properties and relations of the instances should be extracted and formalized as facts in the knowledge base and are used in the reasoning process for the extraction of their semantic features.

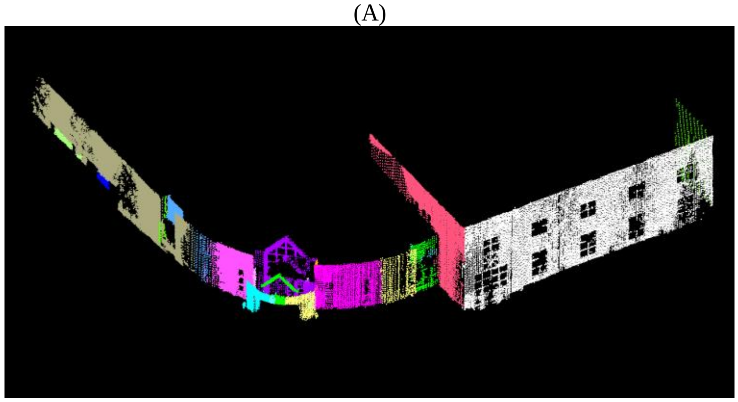
Table 5-4 Rules for the recognition of semantic features of buildings.

Semantic Features	Rules	Explanation	Rule ID
Wall	PlanarRegion(?pr_i), isVerticalTo(?pr_i,?ground), Ground(?ground), hasDirection(?ground,(0,0,1)), hasArea(?pr_i,?area_i), greaterThan(?area_i,2) -> Wall(?pr_i)	A wall is a plane that is vertical to ground and its area it greater than 2 m^2	(6)
	PlanarRegion(?pr_j), isCoplanarTo(?pr_j,?plane_i), Wall(?pr_j) -> Wall(?pr_j)	If a plane is coplanar to a wall, it is wall	(7)
	PlanarRegion(?pr_k), isConnectTo(?pr_k,?pr_i), Wall(?pr_i), isVerticalTo(?pr_k,?ground), Ground(?ground), hasDirection(?ground,(0,0,1)) -> Wall(?pr_k)	If a plane connects to a wall and is vertical to ground, it is wall	(8)
	PlanarRegion(?pr_j), Wall(?pr_i), isConnectTo(?pr_j,?pr_i), isCoplanarTo(?pr_j,?pr_i), -> isSameWall(?pr_j,?pr_i)	If a plane connects to a wall and is coplanar to this wall, they belong to same wall	(9)
Roof	PlanarRegion(?pr_i), hasArea(?pr_i,?area_i), greaterThan(?area_i,2), isSlopeTo(?pr_i,?ground), Ground(?ground), hasDirection(?ground,(0,0,1)), hasSlopeAngle(?pr_i,?ang_i), lessThan(?ang _i,70), hasHeightAttribute(?pr_i,?upperMost) -> ComponentsofRoof(?pr_i)	A roof component has covering function on the uppermost part of a building	(10)
	PlanarRegion(?pr_i), ComponentsofRoof(?pr_j), isSlopeTo(?pr_i,?ground), Ground(?ground), hasDirection(?ground,(0,0,1)), isConnectTo(?pr_i,?pr_j), hasSlopeAngle(?pr_i,?ang_i), lessThan(?ang _i,70), hasHeightAttribute(?pr_i,?upperMost) -> ComponentsofRoof(?pr_i)		(11)
Gable roof style	Set(?B), isInSet(?pr1,?B), isInSet(?pr2,?B), ComponentsofRoof(?pr1), ComponentsofRoof(?pr2), isMeet_Meet_Meet(?pr1,?pr2), Line(?line1) -> hasIntersectLine(?B,?line)	A gable roof consists of two roof sections sloping in opposite directions and the highest, horizontal edges meet to form the roof ridge. (v_g = (0,0,1))	(12)
	Set(?B), isInSet(?pr1,?B), isInSet(?pr2,?B), ComponentsofRoof(?pr1), ComponentsofRoof(?pr2), hasDirection(?pr1,?v1), isLeftSide(?v1,?v_g), hasDirection(?pr2,?v2), isRightSide(?v2,?v_g), Line(?line1), isParallelTo(?line1,?ground), Ground(?ground), hasDirection(?ground,?v_g), higherThan(?line1,?pr1), higherThan(?line1,?pr2) -> GableRoof(?B)		(13)

For instance, the rule (13) in Table 5-4 represents a roof shape shown in Figure 5-16(A). Here, the topological relation between *Pr1* and *Pr2* is “Meet_Meet_Meet_Cover”. Similarly, the relations between *Pr3* and *Pr4* is “Meet_Meet_Meet_Contain”. These two relations are sub-properties of “Meet_Meet_Meet” (see Section 5.5.3.6). Based on the topological relations among planar regions, the *Pr1* and *Pr2* constitute a gable roof because *Pr1* and *Pr2* are connected and they can be added into an instance of the concept “Set”. Then, the reasoning on these instances is executed automatically based on the rule (13) in Table 5-4, which results in the recognition of the semantic features of the roof of the building. Similarly, a gable roof can be recognized from *Pr3* and *Pr4* as well, as presented in Figure 5-16(A). Due to the absence of relevant context information, *Pr5* is recognized as a roof as well. In fact, it is a part of ceiling in reality. In addition, some constraints for defining rules are defined by experiences. This is also true for miss recognition of a tree component as a part of wall.



(A)



(B)

Figure 5-16 Recognition of a roof and its shape (A); and a wall (B) from a point cloud.

In summary, the experiments presented in this section indicate that the designed ontology and the knowledge base are expressive enough and can well represent the knowledge related to different objects in an urban scene. As we can see from these experiments, the proposed knowledge base not only makes use of higher-level generic knowledge of the concepts found in an urban scene but also uses the facts on instances of those concepts obtained from segmentation and assessment of objects in a point cloud. Both of these sets of knowledge are used in the reasoning process for the extraction of semantic features of objects and their components presented in a given urban scene.

5.7 Conclusions and Future Work

In this paper, we have proposed a knowledge-based approach for automatic feature recognition from point clouds in support of the construction of urban virtual geographic environments. In the proposed approach, knowledge about objects in urban scenes is represented by ontology and semantic rules in a knowledge base. The ontology is built based on the steps presented in the METHODOLOGY approach (Fernández-

López, 1997). Due to the advantages of modularity, several modules are defined to organize concepts in the ontology according to different perspectives, such as elevation, functions of objects, source of objects, geometry, composition and spatial relations. In addition, the properties, constraints, and the definitions of relationships among concepts are formally represented. Some theorems in geometry are also expressed as semantic rules for reasoning on spatial relations and other relevant knowledge for object recognition. In the spatial relation module, topological relations for 3D spatial objects are defined and formally represented. Moreover, the topological relations for 3D objects represented by B-Rep are added in the ontology. Based on the concepts, their properties, and their relations, three experiments are conducted to test the competencies of the knowledge base for recognizing complex geometries, recognizing roof shape styles from the planar components of roofs, and recognizing the roof shape from point clouds. The designed experiments demonstrate that the proposed knowledge base can be served to reason on the different objects using the knowledge extracted from point clouds as well as the prior knowledge of the urban scene and its concepts and their relations.

Further investigations will be focused on the reasoning with uncertain and incomplete knowledge bases in the future. This will include fuzzy reasoning based on uncertain information on an urban scene due to missing data and uncertainties in the dataset.

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Introduction of Article

Rule-based Automatic Uncertain Reasoning for Recognizing Building Features based on Uncertain Information Extracted from LiDAR Point Clouds

The point clouds in urban scenes can be incomplete because of occlusions or uneven density, which means that the information extracted from point clouds is uncertain. In the segmentation step, the geometric shapes of object components can be incomplete. Topological relations between object components are uncertain as well. However, in the framework of automatic feature recognition based on a knowledge base in Chapter 5, the formalized knowledge represented by semantic rules cannot reason semantic information of objects from uncertain information extracted from point clouds as shown the challenges in the following figure. In chapter 6, we aim at reasoning on semantic information of objects from uncertain information extracted from point clouds and to evaluate the uncertainties of semantic information based on the semantic rules defined in the knowledge base.

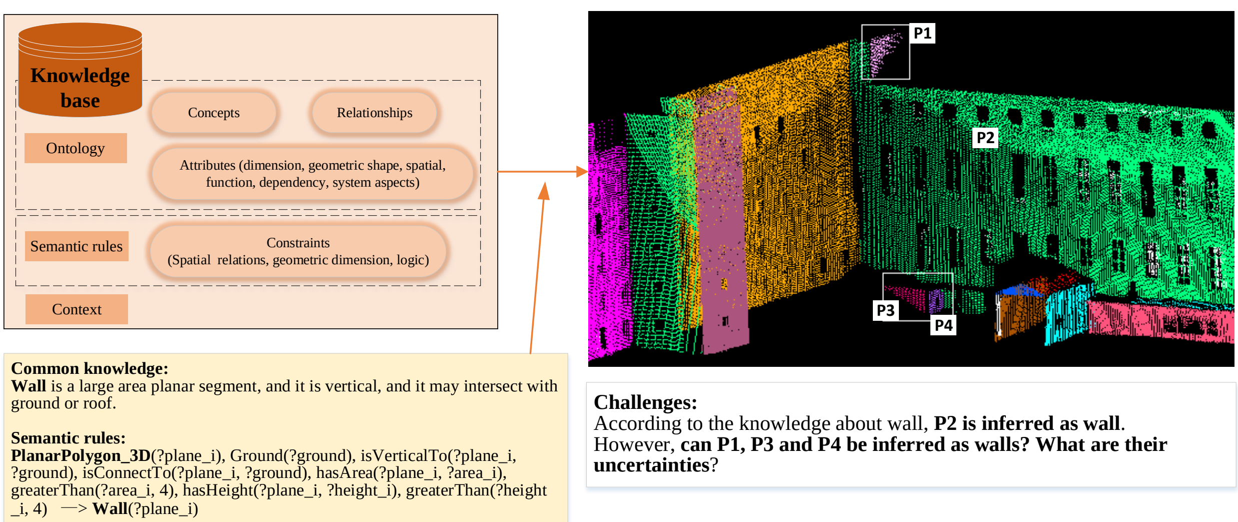


Figure VIII the work to be done for recognizing building features from uncertain information

In this article, a solution for automatic uncertain reasoning of building features (such as walls, roofs, and windows) is proposed to deal with uncertain cases in feature recognition based on the knowledge of buildings. First, a knowledge base is built for representing knowledge about buildings. The rules are defined based on constraints, concepts, properties, and relations. Then the results of object segmentation are transformed into individuals of concepts, including geometric properties, topological relations and geometric relations (coplanar, parallel, vertical, etc.). The similarity evaluation of properties and relations is crucial to assess the uncertainties of properties and relations of transformed individuals compared to those defined in the rules. Based on similarity evaluation, the most appropriate rule is chosen after comparing the similarities of properties and relations in rules and those in individuals. Finally, the Dempster–Shafer (D-S) evidence theory is used to reason building features when the properties and relations are viewed as evidence. The experiment shows that this solution can reason building features from uncertain object components extracted from point clouds. The uncertainties of building features are obtained by the belief of supporting each class and the class with the highest value of belief are chosen as the most probable building feature.

CHAPTER 6 Rule-based Automatic Uncertain Reasoning for Recognizing Building Features based on Uncertain Information Extracted from LiDAR Point Clouds

Xu-Feng XING, Mir Abolfazl Mostafavi, Geoffrey Edwards, Nouri Sabo

6.1 Résumé

La création automatique de modèles géométriques 3D avec des étiquettes sémantiques à partir de nuages de points est un problème complexe, en particulier lors de l'utilisation de nuages de points incomplets, provoqués par une occlusion et des incertitudes lors du processus de segmentation. Dans cet article, nous proposons une approche permettant de reconnaître automatiquement les caractéristiques de bâtiment (par exemple les murs, les toits et les fenêtres) à partir de résultats de segmentation incertains basés sur une connaissance préalable des bâtiments. Les connaissances préalables sur les bâtiments et leurs composants sont représentées sous la forme d'une ontologie et stockées dans une base de connaissances avec un ensemble de règles décrivant les relations entre les bâtiments et leurs composants. Les propriétés géométriques, ainsi que les relations topologiques et géométriques des segments sont représentées dans la base de connaissances en tant qu'individus ou instances de concepts, avec des propriétés et des relations (faits). Les relations géométriques entre les segments extraits de nuages de points sont déterminées à l'aide d'une géométrie projective statistique incertaine. Les relations topologiques entre les segments planaires qu'identifiés à partir des nuages de points sont transformées en représentations formalisées des relations topologiques dans l'ontologie. Ensuite, les méthodes d'évaluation de similarité de propriétés et de relations formalisées sont développées pour sélectionner une règle sémantique appropriée. Enfin, les propriétés et les relations d'un individu donné sont considérées comme la preuve pour le raisonnement sur les caractéristiques de bâtiment dans la théorie de la preuve de Dempster-Shafer (D-S) sur la base des assignations de probabilité de base (BPA) de propriétés et de relations définies par les connaissances des utilisateurs ou les spécifications dans la base de connaissances. Notre solution proposée est capable de raisonner sur les caractéristiques du bâtiment à partir d'une segmentation incomplète et incertaine. Les expériences ont montré que cette approche permettait de construire des entités à partir de résultats de segmentation d'objets fabriqués avec des informations géométriques et topologiques incertaines.

6.2 Abstract

Automatic creation of 3D geometric models with semantic labels from point clouds is a challenging issue, especially when using incomplete point clouds caused by occlusion and uncertainties during the segmentation process. In this paper, we propose an approach for recognizing building features (such as walls, roofs, and windows) from uncertain segmentation results based on prior knowledge of buildings. This prior knowledge of buildings and their components is represented as an ontology and stored in a knowledge base with a set of rules describing the relations between the buildings and their components. Geometric properties, as well as topological and geometric relations of segments, are represented in the knowledge base as individuals, or instances of concepts, with properties and relations (facts). Geometric relations between segments extracted from point clouds are determined using statistical uncertain projective geometry. The topological relations between planar segments identified from point clouds are transformed into formalized representations of topological relations in the ontology. Then, similarity evaluation methods of formalized properties and relations are developed to select a suitable semantic rule. Finally, the properties and relations of a given individual are viewed as the evidence for the building features in the Dempster-Shafer (D-S) evidence theory based on Basic Probability Assignments (BPA) of properties and relations defined by users' knowledge or specifications in the knowledge base. Our proposed solution is capable of recognizing building features from incomplete and uncertain segmentation. The experiments show that this approach is robust for inferring building features from segmentation results of man-made objects with uncertain geometric and topological information.

Keywords: feature recognition, uncertain reasoning, knowledge, semantic rules, Dempster-Shafer (D-S) theory

6.3 Introduction

Due to the increasing need for precise 3D city models at different levels of detail (LOD), automatic 3D modeling from LiDAR point clouds has gained tremendous popularity in recent years. 3D city models provide fundamental spatial information on urban scenes. Applications based on 3D city models, such as evacuation planning (Aedo, 2012), indoor navigation (Isikdag, 2013), and navigation for people with mobility difficulties (Holone, 2008), not only require geometric and topological information about buildings and their components but also about their semantic labels. The automatic creation of semantically enriched 3D building models from LiDAR point clouds is a challenging task. These complexities can be mitigated using prior knowledge of buildings and their components. Specifications and standards for buildings and their components provide very useful information for this purpose including constraints on geometric properties and shapes as well as topological relations between building components. This prior information, as well as the information obtained from the segmentation step, can be used for automatic feature recognition (i.e., the process of semantic labeling of objects and object components) from point clouds.

The formalized representation of knowledge is a fundamental step for knowledge-based automatic feature recognition. An ontology can be used to formally describe concepts and their relations in a domain. Semantic web technology provides tools for a formal description of concepts, terms, and relationships in a specific domain and then allows this information to be shared across applications in a distributed knowledge base system. The ontology's capability of providing machine-processable formalized definitions ensures the sharing of information between applications (Horrocks, 2011). In order to represent formalized knowledge and to build a knowledge base, Web Ontology Language (OWL) (Peter F. Patel-Schneider, 2004) and the Semantic Web Rule Language (SWRL) (W3C, 2004) are designed and recommended to represent formalized knowledge by W3C (W3C, 2012a). Moreover, practical and efficient reasoners, such as Pellet and HermiT, are capable of reasoning based on ontologies and semantic rules. However, one of the limitations of these languages for knowledge representation is that they cannot deal with uncertainty, unreliability, or imprecise knowledge concerning an application domain (Setiawan, 2015). LiDAR point cloud processing includes uncertainties caused by incomplete or uneven point density, which makes it difficult to recognize objects with respect to feature recognition. Hence, in practical applications, the uncertain information extracted from point clouds is not straightforward for reasoning semantic labels of objects in knowledge-based solutions.

In this paper, we propose a rule-based uncertain reasoning solution for feature recognition from the segmentation results of point clouds. Segmentation results of buildings are translated into individuals with geometric properties, geometric relations and topological relations, which all are added into the knowledge base as facts. Additionally, approaches for the similarity evaluation of formalized representations of properties and relations are developed. After comparing the similarities between the relations and properties of individuals and those predefined in predefined semantic rules, the most suitable semantic rule is chosen from the knowledge base. Next, the properties and relations in the selected semantic rule are used for feature recognition. In our proposed solution, the uncertainties of properties and relations are assigned in Dempster-Shafer evidence theory framework based on the user's knowledge or specifications. Similarity evaluation results of properties and relations are applied to reassess the uncertainty of properties and relations based on information extracted from the segmentation results. Finally, the weighted properties and relations are viewed as evidence in order to decide on the semantic labels of building components.

The remainder of the paper is organized as follows: Section 2 will introduce the approaches for feature extraction from point clouds and related works on uncertain reasoning; Section 3 will present the framework of uncertain reasoning for feature recognition and a detailed description of the proposed solution based on similarity evaluation and uncertain reasoning set out in D-S theory; Section 4 will provide an example to demonstrate the experiment results and the final section will outline our conclusions and discuss future research work.

6.4 Related Work

Generally speaking, solutions for feature recognition from point clouds can be classified into two categories: supervised machine learning algorithms (Rusu, 2009a; Wang, 2015; Xiong, 2013), and knowledge-based solutions (Hmida, 2011; Hmida, 2012b; Pu, 2009; Truong, 2013a). Supervised machine learning algorithms require a large number of training sets to train prediction models. The results of these methods are closely dependent on a huge volume of training sets and are generally very costly in computation time. Knowledge-based solutions (Pu, 2006b; Pu, 2009) for feature extraction can be used to recognize building features without the need for training sets. They are effective when dealing with relatively simple building styles and architectural styles defined in a knowledge base. However, they are less efficient with uncertain information.

Urban scenes incorporate both quantitative and qualitative knowledge, such as information on geometric properties of objects, topological relations between components of a complex object or other inherent constraints between objects and their components. The inherent uncertainties in data are related to several factors, including the quality of the measurements or the way they are assessed or modeled. The processing of point clouds introduces uncertainties during segmentation, the extraction of geometric information, and the identification of geometric and topological relations. For the purpose of reasoning in the knowledge base, translating from quantitative information to qualitative information is an essential step for feature recognition. However, classic two-valued semantics (true or false) does not directly allow for representing and reasoning with uncertain and vague knowledge (Bobillo, 2016). Therefore, fuzzy methods (Bobillo, 2011; Bobillo, 2016) are developed based on fuzzy description logics (DLs) to extend classical DLs, aimed at dealing with fuzzy and imprecise information. Hence, new languages and reasoning algorithms need to be developed in order to represent and reason with fuzzy information.

Geometric reasoning with uncertainty can be dealt with using projective geometry at the observation level. After geometric reasoning, geometric relations between segmentation results of buildings are represented as semantic representations (“isParallelTo” and “isVerticalTo”) in the knowledge base. Projective geometry is a mathematical framework used to represent and deal with infinite geometric elements. Geometric reasoning based on statistical projective geometry framework allows one to represent and reason with uncertain geometric relations derived from uncertain observations such as in images and point clouds (Heuel, 2004), taking the uncertainty of observations and error propagation into account as well. For example, hypothesis tests on possible relations between geometric entities as well as geometric constraints for man-made structures have been integrated to determine the boundaries of geometric components of a complex object (Meidow, 2016). Using this method, stairs can be inferred based on projective geometry and Inductive Logic Programming (ILP) (Dehbi, 2011). Additionally, projective geometry has been used to address the uncertainties of creating constraints among components for interactive 3D building models (Loch-Dehbi, 2011). To infer geometric relations between object components detected from point clouds, a method for calculating the uncertainty of a plane was developed based on maximum likelihood and least squares plane estimation (Pathak, 2009). In summary, projective geometry has interesting potential for coping with uncertainty in segmentation results to infer geometric relations between components extracted from point clouds and hence help with feature recognition based on knowledge.

Uncertainty also exists in the process of determining topological relations between geometric primitives segmented from point clouds. The non-uniform point density in point clouds induces uncertainties in shape-based segmentation as well as in the detection of boundaries that introduce uncertainties in the determination of topological relations. Similarity evaluation between topological relations is a way to evaluate this uncertainty. The distance between topological relations has been studied to measure uncertainties of topological relations, such as the morphological distance based on the classified topological relations (Winter, 1996; Winter, 2000), the distance measured by comparing intersection matrices of topological relations represented using Region Connection Calculus (RCC) models (Egenhofer, 1992; Kang, 2004), and the topological distance defined by the number of different places between topological relations represented by 9-Intersection Model (Sabharwal, 2013). Therefore, the distance between topological relations can be used to evaluate uncertainties among topological relations.

Dempster-Shafer evidence theory can be used to cope with different levels of precision without the need for further assumptions because it can directly represent the uncertainty of evidence that can be characterized by a set or an interval of imprecise input. Similarly, the output is also a set or interval. D-S theory allows for the specification of a degree of ignorance, and can be used for inference using an assigned belief for singletons or composites that are viewed as evidence, which makes feature recognition possible from imprecise and inaccurate information based on Basic Probability Assignments (BPA) of properties and relations extracted from point clouds. However, due to the occurrence of conflicts when combining evidence, new combination operations have been developed to solve these conflicts, such as Shafer rules

(Shafer, 1976), Yager's rules (Ronald R, 1987), Zhang's rules (Zhang, 1994), Inagaki's rules (Inagaki, 1991), the mixing or averaging method (Zhang, 1994), weighted evidence (JIA, 2012; Pal, 1993; Xing, 2016a) and so forth. The D-S theory can be used to make decisions from uncertain multisource data. Moreover, the D-S theory has been explored to reason with semantic uncertainty by modeling and representing uncertainty in the ontology (Bellenger, 2011), and in change detection from multispectral images (Shi, 2016; Zhang, 2017). This work provides very good inspiration for our purposes of feature recognition based on knowledge of objects.

6.5 Proposed Framework for Rule-based Automatic Uncertain Reasoning Building Features from Point Clouds

Automatic reasoning on building features from segmentation results involves several steps, including the transformation of quantitative information acquired from segmentation results to semantically formalized properties and relations of individuals in the knowledge base, followed by semantic reasoning based on semantic rules defined in the knowledge base (Figure 6-1). The OWL-based knowledge base consists of ontology and semantic rules. The ontology represents the concepts and their relations. Semantic rules can be used for representing formalized knowledge and reasoning new knowledge with the help of reasoners. In SWRL, rules are represented by an implication between an antecedent (body) and consequent (head). Both the antecedent and consequent consist of zero or more atoms that can be an OWL description (C(x)), OWL property (P(x,y)) and relations (such as sameAs(x,y) or differentFrom(x,y), x and y are variables) (W3C, 2004). The knowledge included in the knowledge base depends on the experience of experts and on practical situations to a great extent. Based on the knowledge base, segments with geometric and spatial information are transformed into individuals of concepts with properties and relations in the ontology. The topological and geometric relationships identified from these results are transformed into relations in the knowledge base. Finally, segment information is transformed and formalized as properties and relations of individuals in the knowledge base. After semantic reasoning, the individuals conforming to the predefined semantic rules can be reasoned as correct building features. This framework of semantic reasoning has been validated (Xing, 2018).

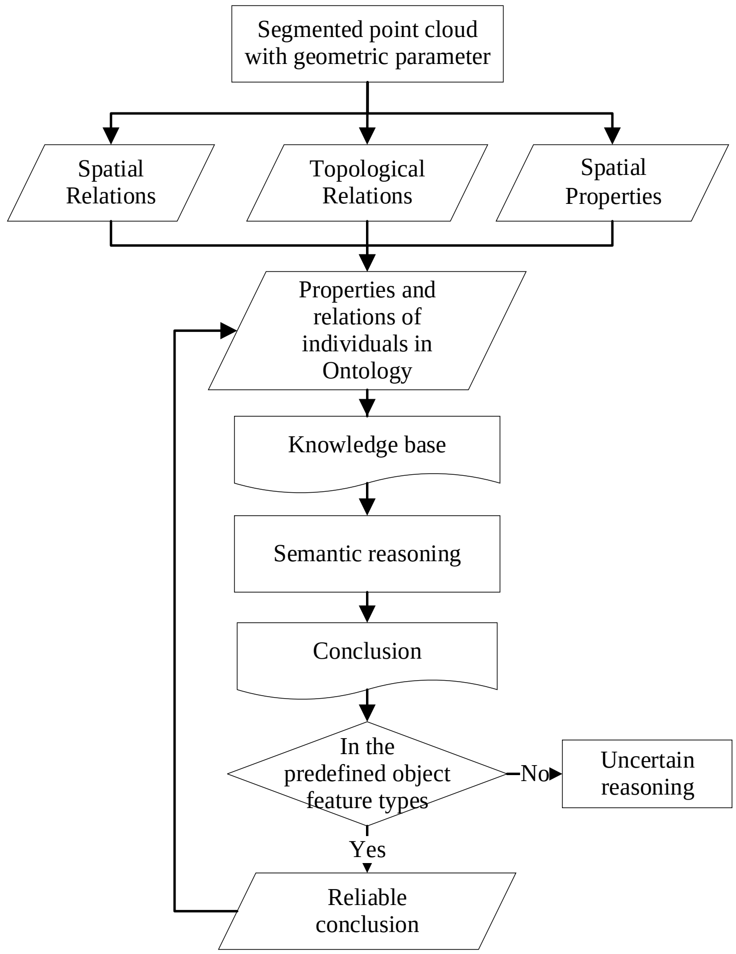


Figure 6-1 Framework of semantic reasoning for building features from segmentation results based on predefined rules

However, in practice, the information acquired from the segmentation process is inherently uncertain. This uncertainty may be introduced during segmentation and detection of topological and geometric relationships of the segments. The properties and relations of individuals with uncertainties may not fit the semantic rules in some cases. The above-mentioned framework of semantic reasoning based on predefined rules cannot deal with the reasoning of building features from individuals with properties and relations transformed from segmentation results with uncertainties because there is no predefined rule for reasoning their building features. Therefore, in this paper, we focus on rule-based uncertain reasoning for feature recognition from segmentation results with uncertainties. Here, we propose a framework for uncertain reasoning for automatic feature recognition from the segmentation results with uncertainties (Figure 6-2).

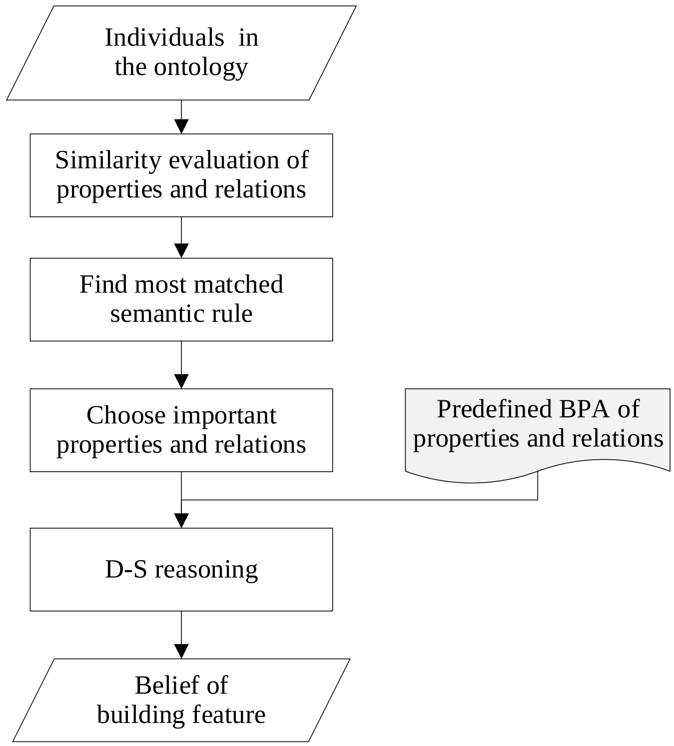


Figure 6-2 Proposed method of uncertain reasoning for building features from segmentation results with uncertainty

- First, we formally represent the geometric and spatial information of segments in the knowledge base. Segments are translated into individuals with properties and relations (Section 6.5.1).
- Then, we compare the similarity between the properties and relations of individuals and those in predefined semantic rules (Section 6.5.2).
- In order to decide which rule is the most probable one for reasoning features, the similarity between properties and relations related to an individual and those contained in the semantic rules is calculated. The cosine distance between vectors is used to evaluate the similarities to determine an appropriate rule for a given individual. (Section 6.5.3).
- The relevant properties and relations defined in the selected semantic rule are chosen as evidence to calculate the belief of supporting specific building features in D-S theory. The feature with the highest belief represents the semantic label for the building component (Section 6.5.4).

6.5.1 Translation of Segments into Individuals in the Ontology

To formalize knowledge representation, OWL and SWRL are used to represent knowledge on buildings including the concepts related to building features and their geometric information, topological relations, and geometric relations. The concepts related to building features are organized under the "Building" concept. In this paper, building component concepts such as "Ceiling", "Wall", "Door", "Roof" and "Column" are the primary carriers to represent building features that can be extracted from point clouds (Figure 6-3). The concept "PlanarPolygon_3D" is used to represent the planar segments representing building components. The properties of individuals of "PlanarPolygon_3D" can be represented as "hasLength", "hasWidth", "hasHeight", "hasArea", "hasBoundary" and so forth. The properties and relations between individuals are presented as well (Table 6-1). The details of the ontology for building a knowledge base are given in (Xing, 2018).

Table 6-1 Modules in ontology for building a knowledge base

Ontology		Examples	Explanation
Concepts	Building components	Ceiling, Wall, Door, Roof, Column	Terms for building components
	Geometry	PlanarPolygon_3D	Terms for geometries in 3D space
Relations	Geometrical relations	isParallelTo, isVerticalTo	Geometric relations between individuals
	Topological relations	T_{p1}-T_{p2}-T_{p3} -T_{p4} (explained in the section 6.5.1.2)	Topological relations between individuals
Properties	hasLength, hasWidth, hasHeight, hasArea, hasBoundary		Properties for describing concepts

The information from segmentation results detected from a point cloud can be quantitative or qualitative and should be formally represented as the properties of individuals for inclusion in the ontology. For the purpose of rule-based uncertain reasoning of building features from segmentation results, segments should be translated into individuals in the ontology and the properties and relations related to the individuals should be considered as facts for reasoning. Thus, we need methods that allow the formal representation of this information in the ontology.

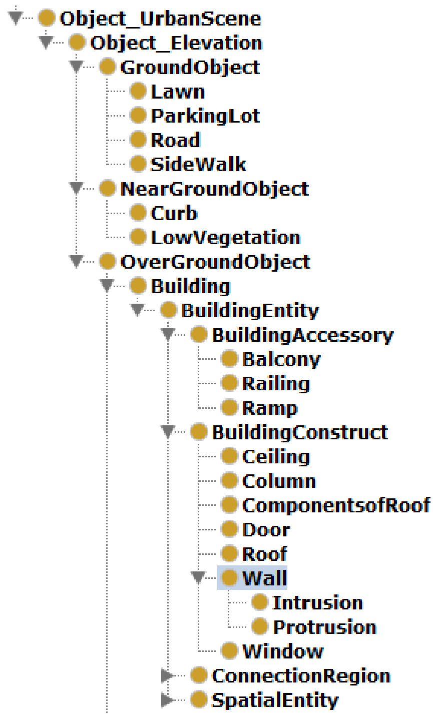


Figure 6-3 Concepts of building features defined in the ontology

6.5.1.1 Transforming Geometric Information from Segments into Properties of Individuals

A planar segment is abstracted as an individual of the "PlanarPolygon_3D" concept. The geometric dimension of the planar segment is directly transformed into properties such as "hasLength", "hasWidth", "hasHeight" and "hasArea". When the boundaries of the planar segment are detected, a boundary estimation can be detected by concave hull polygons based on an angle criterion and Point Cloud Library (Rusu, 2011) can be used for this purpose. The type of polygon detected from the boundaries can be added into the "hasBoundary" property.

6.5.1.2 Transforming Topological Relations into Relations in the Ontology

The topological relations between two planar regions can be described by extended RCC topological relations for 3D object components and can be represented by extended DE-9IM (Xing, 2016b). Differing from the interior, boundary and exterior of a region in 2D, here the interior and boundary of planar regions and the intersection line of two plane equations containing planar regions are the elements of the DE-9IM matrix. The DE-9IM 3*3 topological matrix is defined as follows:

$$T_p'(A,B)=\begin{bmatrix}\dim(A^\circ\cap B^\circ) & \dim(A^\circ\cap\partial B) & \dim(A^\circ\cap Il_B)\\ \dim(\partial A\cap B^\circ) & \dim(\partial A\cap\partial B) & \dim(\partial A\cap Il_B)\\ \dim(Il_A\cap B^\circ) & \dim(Il_A\cap\partial B) & \zeta\end{bmatrix} \qquad \textbf{(Eq 6-1)}$$

Where A° = the interior of the region A

∂A = the boundary of the region A

B° = the interior of the region B

∂B = the boundary of the region B

Il = the intersection line of two planes containing two planar regions

dim() = dimension operator

ζ describes topological relations of two parts of intersection primitives (points and lines) made up by the intersecting line and two planar regions individually.

Apart from the ζ, other elements of the matrix are obtained as DE-9IM cases in 2D space. If there is no intersection, the value of the dimension is -1. If the intersection contains at least one point and no line and an area, the value is 0. Similarly, the value 1 indicates that the intersection contains at least one line segment and no area. The value 2 means that the intersection contains at least one area.

The formalized representation of topological relations between two planar regions is comprised of four parts: $\mathbf{T_{p1}}$- $\mathbf{T_{p2}}$- $\mathbf{T_{p3}}$- $\mathbf{T_{p4}}$. $\mathbf{T_{p1}}$ is the overall topological relation between two planar regions, including disjoint, meet, intersect. $\mathbf{T_{p2}}$ is the relation between planar region A and the intersection line, including disjoint, meet, overlap. $\mathbf{T_{p3}}$ is the relation between planar region B and the intersection line, including disjoint, meet, overlap. $\mathbf{T_{p4}}$ is the topological relation of primitives (intersection primitives such as points line segments) on the intersection line (Xing, 2016b). The possible relations between two points on the intersection line are disjoint or equal. The possible relations between a line segment and a point are disjoint, meet and contain. The possible relations between two line segments are disjoint, meet, overlap, cover, contain and equal.

For the purpose of semantic reasoning from a knowledge base, the topological relations represented by DE-9IM, calculated by numeric computation, should be transformed into formalized representations of topological relations in the ontology. To obtain the formalized representation of topological relations, the submatrix consisting of the intersection operation among the interior and boundaries of two planar regions is chosen to decide on the first part (T_{p1}) of the formalized representation of the topological relations. The submatrix is presented as follows:

$$T_{2\times 2}(A,B)=\begin{bmatrix}\dim(A^\circ \cap B^\circ) & \dim(A^\circ \cap \partial B)\\ \dim(\partial A \cap B^\circ) & \dim(\partial A \cap \partial B)\end{bmatrix} \qquad \textbf{(Eq 6-2)}$$

For "disjoint", the submatrix elements are [-1,-1; -1,-1]. For "meet", the elements are [-1,-1; -1, *]. Here, * could be 0 or 1. For "intersect", the elements are [# ,*; *, #] (# indicates the value of elements, which could be -1, 0, 1).

The second (T_{p2}) and third parts (T_{p3}) of formalized representations of topological relations are dependent on the relations between planar regions and the intersection line. Similarly, the submatrix, consisting of the intersection operation among the interiors, boundaries of planar regions and the intersection line, is used to decide on their topological relations:

$$T_{2\times 1}(A,Il)=\begin{bmatrix}\dim(A^\circ \cap Il)\\ \dim(\partial A \cap Il)\end{bmatrix} \qquad \textbf{(Eq 6-3)}$$

For the "disjoint" of planar region A and the intersection line, the submatrix elements are [-1,-1;]. For "meet", the elements are [-1,*;]. Here, * could be 0 or 1. For "overlap", two elements are [1, *]. Similarly, the third part can be acquired in the same way.

The fourth part (T_{p4}) of the formalized representation of topological relations relies on the geometric information of the common parts made up of two planar regions and the intersection line. The relations between point and point, point and line, and line and line are all listed in (Xing, 2016b). Finally, the topological relation between two planar regions is formalized as $\mathbf{T_{p1}}$**-**$\mathbf{T_{p2}}$**-**$\mathbf{T_{p3}}$ **-**$\mathbf{T_{p4}}$ in the knowledge base from point clouds.

6.5.1.3 Transforming Geometric Relations between Segments into Relations between Individuals in the Ontology

Geometric relations among planar segments are determined based on the estimation of the geometric primitives' equations. These numeric parameters are used to determine the geometric relations (e.g., the angle between the normal vectors of two planes for determining the "parallel" or "vertical" relations). However, geometric relations must be formalized as semantic descriptions like "isParallelTo" or "isVerticalTo" in the ontology. To achieve this, statistical uncertain projective geometry offers a formal representation of geometric entities and a framework for reasoning geometric relations among entities from observations. Due to the need for identifying geometric relations (parallel, vertical) directly from point clouds, statistical uncertain projective geometry is used for transforming geometric relations detected from segmentation results into semantic representations in the ontology.

In statistical uncertain projective geometry, a geometric entity can be constructed with a pair of homogeneous vectors and a covariance matrix. Geometric relations are first constructed based on homogeneous representations of geometric entities in projective geometry. The constructed relations are regarded as a hypothesis. Testing this hypothesis helps to determine the geometric relations between uncertain geometric entities. In a point cloud, a plane can be detected directly from points. The uncertainty of a plane is closely related to the quality of point clouds. A plane equation is represented as $aX + by + cZ + d = 0$, and its homogeneous representation is $(a \ b \ c \, ; \mathrm{d})$. The covariance matrix of a plane can be represented as follows:

$$\sum_{pp} = \begin{pmatrix} \delta_a^2 & \delta_{ab} & \delta_{ac} & \delta_{ad} \\ \delta_{ab} & \delta_b^2 & \delta_{bc} & \delta_{bd} \\ \delta_{ac} & \delta_{bc} & \delta_c^2 & \delta_{cd} \\ \delta_{ad} & \delta_{bd} & \delta_{cd} & \delta_d^2 \end{pmatrix} \quad \textbf{(Eq 6-4)}$$

We propose to evaluate the uncertainty of a plane using the normal estimation of point clouds. If a set of points are detected as a plane from a point cloud, the covariance matrix of this plane can be acquired using the surface normal computed in each point in the point cloud and the distance from the points to the plane. Here we assume that the surface normal estimation is independent from the parameter *d* in the plane equation. Thus, the elements δ_{ad} , δ_{bd} , δ_{cd} all are 0 in the covariance matrix. Additionally, in plane detection, δ_d^2 is related to the distance threshold between the points and the plane.

Based on the representation of uncertain geometric entities, a hypothesis test of geometric relations between geometric entities is concluded by a given significance level. If the hypothesis is not rejected, we consider that this geometric relation holds. Finally, based on the outcome of this hypothesis test, geometric relations between geometric entities with homogeneous representations are formalized as relations between individuals in the ontology, such as “isParallelTo”, “isVerticalTo”. For example, two plane equations are obtained based on segmentation results. The geometric relation “parallel ” between two planes cannot be rejected at a significance level of 5%. Thus, we can conclude that the “parallel” relation holds with the probability of 95%. The geometric relation is translated into a “isParallelTo” relation between two individuals in the ontology.

6.5.2 Similarity Evaluation of Properties and Relations at the Semantic Level

The topological and geometric relations obtained from segmentation results can differ from those predefined in the knowledge base due to uncertainties. In our proposed solution for uncertain reasoning for inferring building features, similarity evaluations between transformed properties or relations from segmentation results and those predefined in the semantic rules are crucial to measuring uncertainties at the semantic level. For properties related to numeric geometric information, similarity can be evaluated by $1-|val-Th|/Th$ (val is the given value and Th is the defined threshold).

6.5.2.1 Similarity Evaluation between Semantic Representations of Geometric Relations

If the geometric relation concluded by statistical uncertain projective geometry cannot be rejected, the semantic representation of geometric relations could be "isParallelTo" or "isVerticalTo" after translation. If this relation is the same as the one defined in the rules, the similarity between them is defined as 1. Similarly, the similarity between "isParallelTo" or "isVerticalTo" is 0.

However, if the geometric relations (parallel, vertical) are rejected, the angle between the normal of planes is used to evaluate the similarity of geometric relations (parallelity and perpendicularity). The formula for evaluating the similarity of parallelity is as follows:

$$S_{\parallel}=\begin{cases}1-\dfrac{\theta}{90}, & 0\le\theta\le 90^\circ\\ 1-\dfrac{180-\theta}{90}, & 90^\circ<\theta\le 180^\circ\end{cases} \qquad \textbf{(Eq 6-5)}$$

Where $S_{\parallel}$ indicates the similarity of the parallelity relationship. θ is the angle between the two planes. For example, if the angle is 65^{o} after numeric computation but it cannot be concluded as "isParallelTo", the similarities of parallelity is 0.278. In this definition, when the angle between two planes is 0°, the similarity of parallelity is defined as 1. However, when the angle is 90°, the similarity is 0. This definition conforms to the similarities between semantic representations of geometric relations.

Similarly, the formula for evaluating the similarity of perpendicularity is defined as follows:

$$\mathrm{S}_{\perp}=1-\frac{|\theta-90|}{90} \quad 0^\circ\le\theta\le 180^\circ \qquad \textbf{(Eq 6-6)}$$

In summary, the similarity between the geometric relations concluded by numeric computation and those predefined in the ontology can be determined based on statistical uncertain projective geometry and the proposed formulas.

6.5.2.2 Similarity Evaluation of Topological Relations with Semantic Representation

6.5.2.2.1 Definition of the Distance between Semantic Representations of Topological Relations

The similarity between topological relations is evaluated based on the distance between semantic representations of topological relations which indicates the distance between the formalized representations of topological relations and the ones computed from segmentation results. Thus, the distance is defined by the steps of the topological transition (Randell, 1992). As mentioned, the formalized representation of topological relations in the ontology is decomposed into four parts for two planar regions: T_{p1}, T_{p2}, $T_{p3,}$ and T_{p4}. For example, the formalized representation of the first topological relation defined in the ontology (T_{ra}) is $T^a_{p1} - T^a_{p2} - T^a_{p3} - T^a_{p4}$, for example, "Disjoint-Meet-Meet-Equal", and the second one extracted from segmentation results (T_{rb}) is represented as $T^b_{p1} - T^b_{p2} - T^b_{p3} - T^b_{p4}$, for example, "Disjoint-Meet-Overlap-Cover". Because T_{p1} describes the overall spatial relation between planar regions, it will not be part of the similarity evaluation. Thus, the distance of formalized topological relations between two planar regions is determined by the differences of the last three parts of formalized representations of topological relations. Herein, the distance of two formalized representations of topological relations is defined as follows:

$$d_t = d_1 + d_2 + d_3 \qquad \textbf{(Eq 6-7)}$$

Where $d_1 = d(T^a_{p2}, T^b_{p2})$, $d_2 = d(T^a_{p3}, T^b_{p3})$, $d_3 = d(T^a_{p4}, T^b_{p4})$.

6.5.2.2.2 Calculation of d_1 and d_2

d_1 and d_2 are calculated by the distance of topological relations between a planar region and the intersection line, including Disjoint, Meet, and Overlap. According to the number of transitions steps in topological relations, the distance between "disjoint" and "meet" is 1, the distance between "meet" and "overlap" is 1 and the distance between "disjoint" and "overlap" is 2. The distance matrix for querying d_1 and d_2 is presented in Table 6-2.

Table 6-2 The distance matrix for calculating d_1 and d_2

	Disjoint	Meet	Overlap
Disjoint	0	1	2
Meet	1	0	1
Overlap	2	1	0

6.5.2.2.3 Calculation of d_3

To calculate the value of d_3, all possible relations in the fourth part (T_{p4}) presented in (Xing, 2016b) are classified as five clusters (Figure 6-4) based on the topological transition step. Following the movement sequence of two primitives on a line, their orders are Disjoint, Meet, Overlap, Cover, Equal and Contain. The distance matrix for the topological relations transition corresponding to Figure 6-4 is shown in Table 6-3.

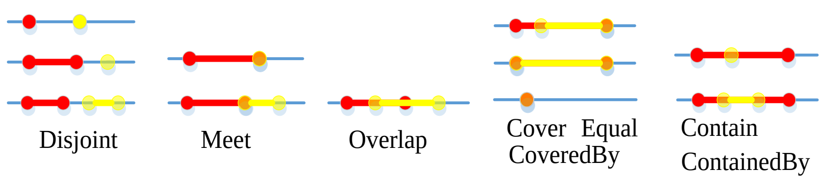


Figure 6-4 A graphical representation of topological relations transitions

Table 6-3 The distance matrix for calculating d_3

	Disjoint	Meet	Overlap	Cover	Equal	Contain
Disjoint	0	1	2	3	3	4
Meet	1	0	1	2	2	3
Overlap	2	1	0	1	1	2
Cover	3	2	1	0	0	1
Equal	3	2	1	0	0	1
Contain	4	3	2	1	1	0

However, when the distance evaluated by topological transitions between two formalized representations of topological relations is 0, there are still some differences in geometric information between two geometric primitives. For example, in Figure 6-5, the formalized representation of topological relations for case (A) "Meet-Meet-Meet-Equal" is defined in the ontology and (B) "Meet-Meet-Meet-Cover" is identified from segmentation results. Thus, the similarity between two relations needs to be evaluated using the differences in their geometric information.

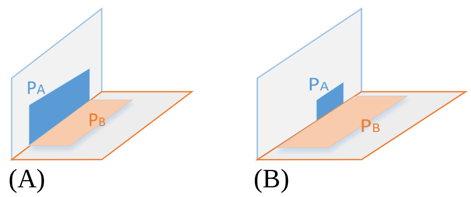


Figure 6-5 The difference of geometric information for topological relations whose distance is 0

The distance based on the geometric information d_g can be evaluated by the positions of the endpoints of the line segments located on the intersection line. The ratio of three parts (L_1, L_2 and L_3) separated by four endpoints on the maximum length of line segments on the line (L) (as shown in Figure 6-6) is chosen as the geometric characteristic to distinguish between them. The geometric characteristics can be represented as a vector $v_g = (L_1/L,\ L_2/L,\ L_3/L)$. Their distance d_g is calculated by the Euclidean distance between two vectors. Then, the distance d_g will be changed in the steps of topological transition.

$$d_g = d(v_{g1}, v_{g2}) \qquad \textbf{(Eq 6-8)}$$

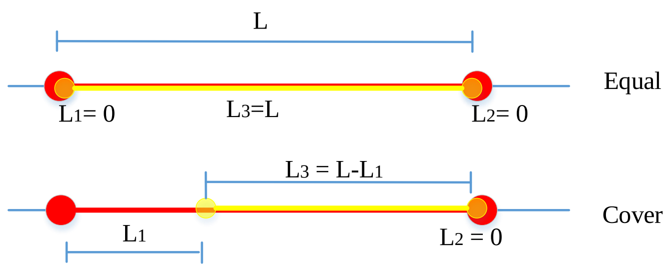


Figure 6-6 Graphical description of the feature vectors of Equal and Cover relations

Mapping d_g into the Topological Transition step

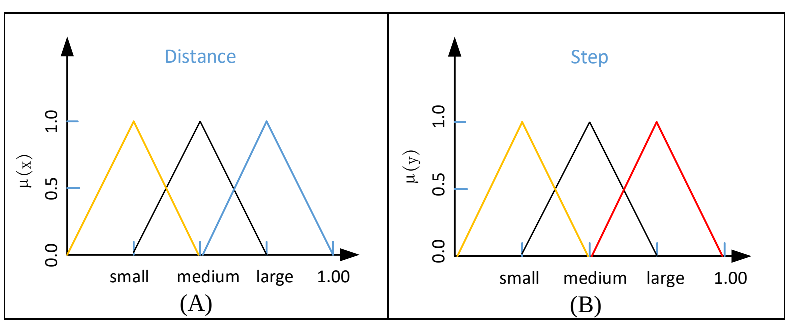
Due to the distance defined by the topological transition to evaluate similarities between semantic representations of topological relations, the distance based on geometric information (d_g) must be changed into the steps of topological transition (d_t). For this purpose, we propose to transform the distance d_g into the steps of topological transition using fuzzy logic. First, the distance between vectors d_{vec} is normalized as follows:

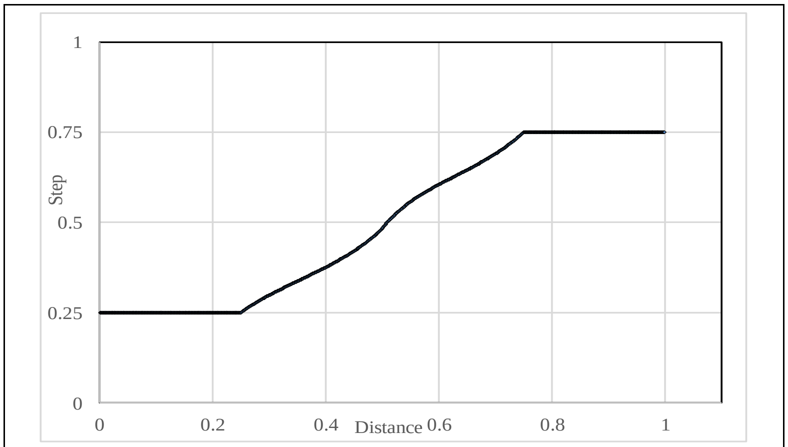
$$d_{norm\_g} = \frac{d_g - d_{g\_\min}}{d_{g\_\max} - d_{g\_\min}} \qquad \textbf{(Eq 6-9)}$$

Here the distance d_g has the minimum value 0 ($d_{g\_\min}$) and the maximum value $\sqrt{2}$ ($d_{g\_\max}$) for the ideal case. Hence, the range of normalized distance is between 0 and 1. Then the normalized distance d_{norm_g} is considered the input of fuzzy logic. The input and output linguistic variables are assigned by the definition of membership functions (Figure 6-7). The fuzzy set consists of linguistic terms representing the degree of distance [small, medium, large]. The input values are in the range [0, 1] and they are covered with the overlapping range defined as small [0, 0.5], medium [0.25, 0.75] and large [0.5, 1.0]. The output range is set at [0, 1]. Thus, the output values are covered by small [0, 0.5], medium [0.25, 0.75] and large [0.5, 1]. Based on these definitions, a crisp input value x is fuzzified and translated into the degree of membership in each fuzzy set. After using the inference rules, the results are linked to the input values. Here, the inference rules are defined as follows (Distance indicates normalized distance d_{norm_g} and Step means the step of topological transition):

- If Distance is small, then Step is small
- If Distance is medium, then Step is medium
- If Distance is large, then Step is large

In the inference stage, the fuzzy input values trigger the inference rules to generate the fuzzy output values. Lastly, the fuzzy outputs are translated into crisp values using a defuzzifier. At this stage, the common used Mamdani controller is used as a fuzzy logic operator to compute the centroid as the output values. The relation between the input and output is described in Figure 6-7C. Unlike the general steps of topological transition, the result after fuzzy reasoning is mapped to a continuous value in the range [0, 1]. Finally, the distances between formalized representations of topological relations are comparable to the steps of topological transition.





(C)

Figure 6-7 Definitions of membership functions (distance (A) and step (B)) in fuzzy logic; the relation between input and output (C)

6.5.2.2.4 Calculation of the Similarity between Formalized Semantic Representations of Topological Relations

The distance defined by the topological transition between formalized semantic representations of topological relations is used to measure their similarity and evaluate the uncertainties of topological relations identified from segmentation results compared to those defined in the ontology. The distance between topological relations is first normalized in order to calculate the similarity. The normalization method is as follows:

$$d_{norm} = \frac{d_t - d_{\min}}{d_{\max} - d_{\min}} \quad \textbf{(Eq 6-10)}$$

Here, the distance defined by the topological transition step has the minimum value 0 and the maximum value 8 because d_1 and d_2 have the maximum value 2, and d_3 has the maximum value 4. Finally, the normalized distance is in the range between 0 and 1.

The similarity between topological relations is defined as follows:

$$S_{top} = 1 - d_{norm} \quad \textbf{(Eq 6-11)}$$

Finally, through the similarity evaluation, the degree of closeness between the formalized representations of topological relations is calculated.

6.5.3 Selection of Semantic Rules based on Similarity Evaluation

The knowledge of building features is formalized as semantic rules in the knowledge base. The SWRL semantic rules are represented as a "Human Readable Syntax" form:

$$a_1 \wedge a_2 \wedge ... \wedge a_n \Rightarrow consequent$$

Where a_i indicates the atom of the antecedents (body). The antecedents and consequents may be classes, relations, properties, or individuals. In the knowledge base, we consider the predefined semantic rules as reference knowledge. The individuals, properties, relations and some constraints defined in the semantic rules are definite. However, the properties and the relations of individuals transformed from the segmentation results based on their geometric and spatial information extracted from point clouds can be uncertain. Therefore, in our proposed solution, choosing the critical properties and relations as evidence is the key step for uncertain reasoning in the D-S theory.

For this purpose, all the antecedents in the rules are considered a vector. In this vector, the elements represent the similarity of each atom of antecedents in the rules. Because the predefined rules are prior knowledge and used as references to calculate the similarity, all the elements in the vector are 1. Thus, for each defined rule, the similarity vector for selected rules is organized as a vector $ref = (1,1,...,1)$, and the number of elements depends on the number of atoms of antecedents. For a given individual, according to the similarity measurement between properties and relations of individuals and the corresponding antecedents in the rule, the similarity vector of an individual is defined as $S = (S_1, S_{2,} ..., S_n)$. The number of elements in the vector is equal to that in the ref. All the elements are in the range between 0 and 1. Based on two vectors, we use the cosine value of these two vectors as the criterion to decide which rule is suitable for drawing the conclusion. The cosine value of these two vectors indicates the similarity of two non-zero vectors. The formula for computing the consistency of information of an individual ind_i and a semantic rule r_j is defined by the cosine value of two vectors: $S = (S_1, S_{2,} ..., S_n)$ and $ref = (1,1,...,1)$.

$$C(ind, r) = \cos(\theta) = \frac{\sum_{k=1}^{n} S_k}{\sqrt{\sum_{k=1}^{n} {S_k}^2}\sqrt{n}} \qquad \textbf{(Eq 6-12)}$$

When the value $C(ind_i, r_j)$ is closer to 1, the provided information for individuals shows more similarity to the semantic rule. Here, we choose the angle of two vectors to define the similarity.

$$Similarity(ind,r) = 1 - \frac{\cos^{-1}(C(ind,r))}{\pi} \quad \textbf{(Eq 6-13)}$$

Finally, the most suitable rule for reasoning the features can be chosen using the computation of the similarity.

6.5.4 Uncertain Reasoning based on Similarity Evaluation

Uncertain reasoning is based on the similarity evaluation. For this purpose, a suitable semantic rule should be chosen. This is done according to the transformed information of an individual and the similarity evaluation. The properties and relations in the semantic rules are viewed as crucial evidence. The key step for using these crucial properties and relations to conduct uncertain reasoning in the D-S evidence theory is to evaluate the similarities between the properties and relations of individuals and those defined in the chosen semantic rule. However, the results of the similarity evaluation are largely dependent on the uncertainties in point clouds.

To conduct uncertain reasoning in the D-S evidence theory, some predefined Basic Probability Assignments (BPAs) of properties and relations in semantic rules should be assigned according to prior knowledge, which is a key step in translating semantic rules into beliefs of properties and relations in this theory. The BPAs of properties or relations with various constraints are predefined by users' knowledge about building features and some specifications, such as a wall, which is a large planar segment that is vertical to the ground. A roof is composed of planar segments that are located above walls or that connect to walls. As shown in Table 6-4, building features (F_1, F_2, …, F_m) can contain a single feature or a set of features. Then, the properties and relations in the selected semantic rule are viewed as evidence. The similarity evaluation between the properties and relations of individuals and those predefined in the selected semantic rules is used as a weight of corresponding BPAs of properties and relations of individuals. The weighted BPAs of properties and relations reveal the degree of importance of each property or relation. Finally, the weighted BPAs of properties and relations of individuals are used to infer the possible building features. Due to the possibility of conflicts during the combination of evidence, we choose the method proposed in (JIA, 2012) that first detects the conflict and then reassess the weights of evidence to deal with the case of high conflict among the evidence.

Table 6-4 Definition of BPAs of properties and relations (F indicates building features, P indicates properties, R indicates relations, X indicates BPAs of properties and relations)

		BPAs of Building Features				
Property or relation	Constraints	F1	F2	F3	…	Fm
P1	≥ a1	X^1_{p1}	X^2_{p1}	X^3_{p1}	…	X^m_{p1}
P2	≤ b1	X^1_{p2}	X^2_{p2}	X^3_{p2}	…	X^m_{p2}
R1	Fi	X^1_{R1}	X^2_{R1}	X^3_{R1}	…	X^m_{R1}
R2	Fj	X^1_{R2}	X^2_{R2}	X^3_{R2}	…	X^m_{R2}
…	…	…	…	….	…	…

6.6 Experiments and Results

Our experimental datasets were observed by a mobile terrestrial LiDAR scanner on the campus of Laval University. The dataset contains mostly vertical components of objects. Since laser pulses can pass through glass windows, indoor objects facing windows were recorded as well. Additionally, due to the occlusions, some components of objects may be incomplete or missing.

6.6.1 Definition of Semantic Rules for Recognizing Building Features

Based on the ontology mentioned in Section 6.5.1, the required concepts, such as "Wall", "Roof", "Protrusion" and "Intrusion" were selected to represent building features. The concept related to geometry, for example, "PlanarPolygon_3D" was chosen to represent planar segments obtained after segmentation results. Another concept, "Ground" was needed to represent the ground. Geometric relations, such as "isVerticalTo" and "isParallelTo" defined in the ontology were used to represent the identified geometric relations between planar segments. The topological relations conformed to the formalized representation of the topological relations. The properties related to geometric information were formalized as "hasHeight", "hasArea" and so forth. Semantic rules are one of the primary components of a knowledge base. In this experiment, some rules were formalized based on the above-mentioned concepts, properties, and relations. The following common knowledge is defined to recognize main building features (Pu, 2009) (walls, roofs, etc.)

- A wall is a large area planar segment; it is vertical and may intersect with the ground or a roof.
- A roof is a large area segment located above a wall's upper boundary edge, or a roof intersects with a wall's upper boundary edge.
- A protrusion is a small area outside the wall or roof; one facet is parallel to the wall, and its left and

right facets connect to the wall with a sharp angle.

- An intrusion is a small area inside a building, with one facet parallel to the wall.

To present the steps of our proposed method, we can provide some examples of semantic rules for reasoning walls from point clouds. Here we define two rules for identifying walls from planar segments of buildings. The first rule describes the case where a planar segment can be identified as a wall when it is vertical to the ground, has an area larger than a_1 m^2 and a height greater than h_1 meters, and connects to the ground. The second rule means that a planar segment can be recognized as a wall when it is vertical to the ground, has an area is larger than a_2 m^2, and meets with another wall. Here a_1, h_1 and a_2 can be set by the architecture specifications or by users depending on their specific environments. In this paper, we set a_1, and a_2 to 4 m^2, and h_1 to 4 meters. These two rules are represented by SWRL rules as follows:

Rules	RuleID
PlanarPolygon_3D(?plane_i), Ground(?ground), isVerticalTo(?plane_i, ?ground), isConnectTo(?plane_i, ?ground), hasArea(?plane_i, ?area_i), greaterThan(?area_i, 4), hasHeight(?plane_i, ?height_i), greaterThan(?height _i, 4) → Wall(?plane_i)	(1)
PlanarPolygon_3D(?plane_i), Wall(?plane_j), Ground(?ground), isVerticalTo(?plane_i, ?ground), isMeet_Meet_Meet_Equal_To(?plane_i, ?plane_j), hasArea(?plane_i, ?area_i), greaterThan(?area_i, 4), hasHeight(?plane_i, ?height_i), greaterThan(?height _i, 4) →Wall(?plane_i)	(2)

6.6.2 Transforming Quantitative Information of Segments into Properties and Relations of Individuals

The experimental input data are planar segments with geometric parameters as shown in Figure 6-8. A zoomed-in image of the input dataset of planar segments is shown in Figure 6-9. There are three small planar segments that are difficult to recognize as walls by the semantic rules. They are labeled using white rectangles. Each planar segment can be represented by a plane equation. Meanwhile, the boundaries of planar segments can also be extracted. Based on this information, the topological relations of planar segments are extracted using the extended RCC topological relations among 3D complex object components (Xing, 2016b).

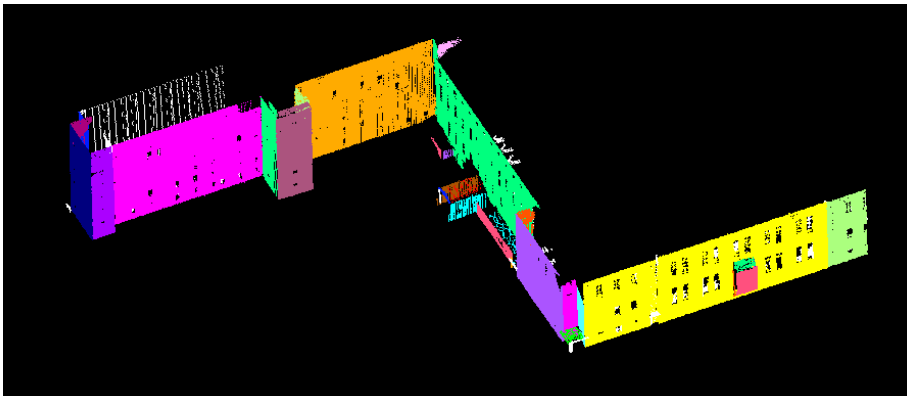


Figure 6-8 Segmentation results of a part of building from a point cloud

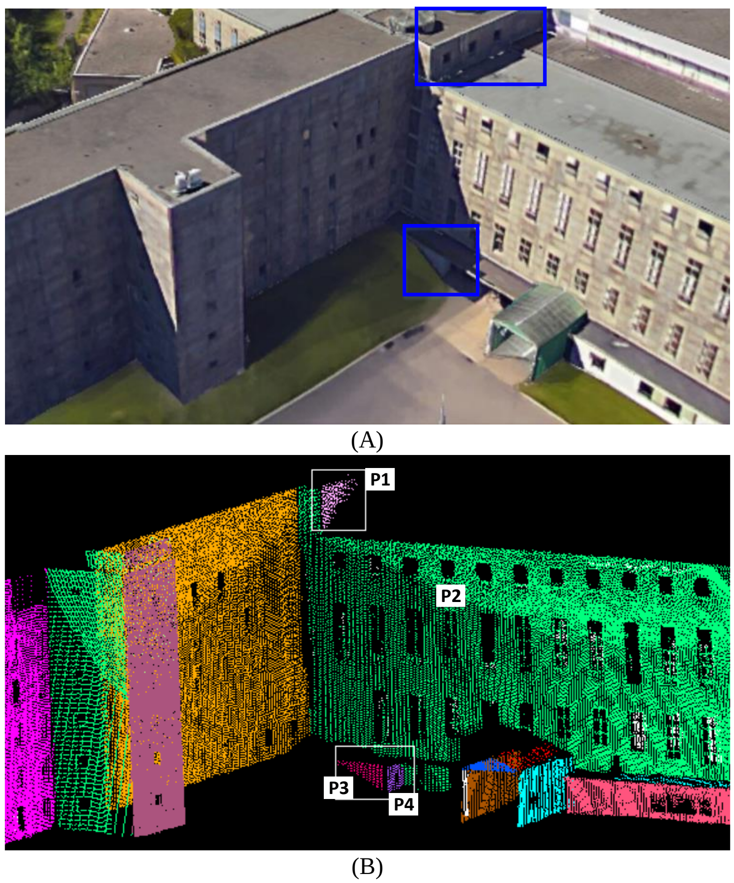


Figure 6-9 Zoomed segmentation results. (A) image from Google Earth; (B) small planar segments in the segmentation results

Here, we choose a pink planar segment (P1) labeled in the top white rectangle as an example to validate our proposed method for recognizing building features from uncertain information. First, the geometric information of planar segments can be obtained by numeric computation (Table 6-5). In our experiment, the parameters of the plane equation are estimated using a random sample consensus (RANSAC) algorithm with the plane model. In the RANSAC algorithm, the points fitting a plane model are considered inliers, and the parameters of the plane equation are estimated from these inliers.

Table 6-5 Geometric information from planar segments after numeric computation

Planar Segment	Neighboring planar segment	Height(m)	Area(m^2)	Angle between plane normal and ground plane (in degrees)	Connect to the ground?	Angle between a plane normal and its neighbors (in degrees)
P1	P2	3.41	4.7	89.91	No	89.88
P2	P1	21.50	190.64	90.09	Yes	89.88

Based on the geometric information from planar segments P1 and P2, statistical uncertain projective geometry is used to determine if their geometric relationship (parallelity or orthogonality) holds using hypothesis testing. The representation of a planar segment consists of a pair of geometric entities and its covariance matrix. The covariance matrix of a plane is calculated by the normal estimation of the inliers of a planar segment. In our experiment, the parameters of P1 are represented as a pair of the homogeneous representation of plane equation parameters and its covariance matrix is as follows:

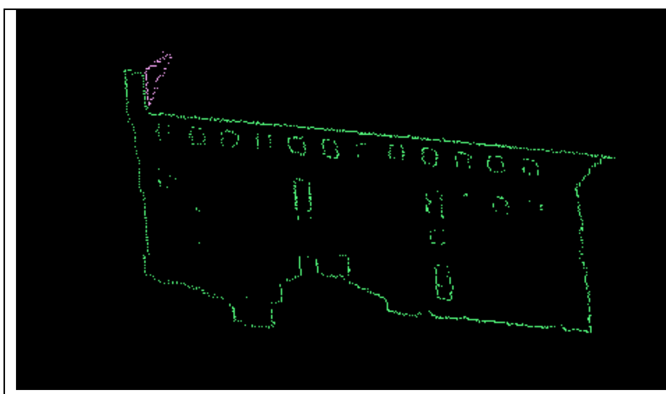
$$P1 = \left((0.791,\ 0.612,\ 0.00155,\ 19.9),\ \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.002 & 0 \\ 0 & 0 & 0 & 0.01 \end{bmatrix} \right)$$

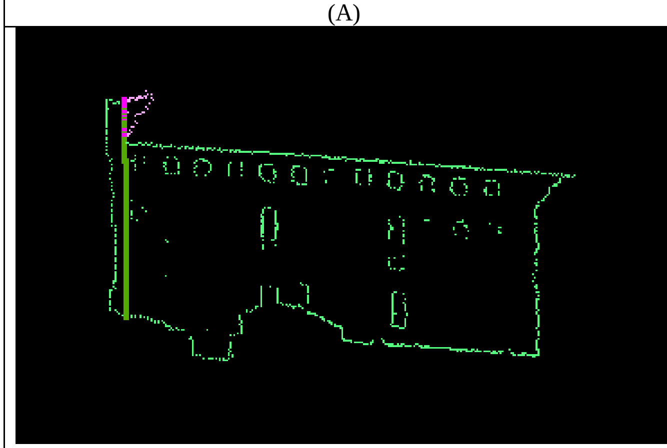
Similarly, the planar segment P2 is represented as follows:

$$P2 = \left((0.610,\ -0.792\ -0.00156\ -0.438),\ \begin{bmatrix} 0.217 & -0.281 & -0.00561 & 0 \\ -0.281 & 0.378 & 0.00701 & 0 \\ -0.00561 & 0.00701 & 0.0048 & 0 \\ 0 & 0 & 0 & 0.01 \end{bmatrix} \right)$$

The hypothesis of orthogonality between P1 and P2 is tested with a significance level of 95%. Since the test result is 0.075 and less than the threshold of 3.748, this hypothesis cannot be rejected. Thus, the geometric relation that P1 and P2 are orthogonal holds. Likewise, we conclude that P1 and P2 are perpendicular to the ground.

Additionally, the boundaries of planar segments are necessary for detecting their topological relations. The boundaries of P1 and its neighbor P2 are extracted from points (Figure 6-10(A)). After obtaining topological relations by the method proposed in (Xing, 2016b), the intersection line of the two planes is calculated based on the geometric parameters of planar segments (Figure 6-10(B)). Additionally, the common parts of planar segments and the intersection line are extracted as shown in Figure 6-10(C). Based on these results, the topological matrix representing topological relations is calculated as [-1 -1 1; -1 1 1;-1 1 ζ]. The ζ is dependent on the geometric information from the boundaries of two planar segments on the intersection line. According to their geometric information, the distance from the endpoints of two line segments is 0.222 m (Figure 6-11). For determining whether two points coincide or whether they are on the line, the threshold is defined using the average distance between it and its k-nearest neighbors. We choose k=6 to calculate the average distance between the current point and its neighbors. If the distance between two endpoints is less than this average distance, the points can be viewed as coincident. Here, the threshold of the average distance is calculated as 0.2285. Therefore, these two endpoints coincide. Finally, the topological relation between P1 and P2 is Meet-Meet-Overlap-Cover.


(A)


(B)

(C)

Figure 6-10 Results of the steps for detecting topological relations from point clouds

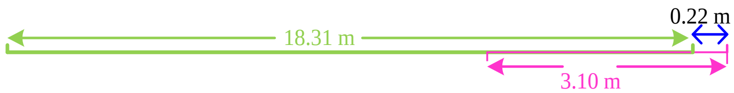


Figure 6-11 Line segments on the intersection line for determining topological relations

Based on previous information on P1 and P2, the planar segments are transformed into individuals P1 and P2 in the ontology. Their properties and relations to other individuals are formalized as shown in Figure 6-12. After semantic reasoning, P2 can obviously be inferred as a wall using the first semantic rule predefined in Section 6.6.1. However, P1 cannot be recognized as a wall because its height is less than the predefined constraints of this property and it does not connect to the ground. According to our proposed method, in the following step, we will compare the similarity of transformed properties or relations of individuals and those defined in the semantic rules for choosing properties or relations in the selected semantic rules for uncertain reasoning.

P1

hasHeight	**3.42**
hasArea	**4.7**
isVerticalTo	**ground**
isConnectTo	**P2**
isVerticalTo	**P2**
isMeet_Meet_Overlap_Cover_To	**P2**

(1)

P2

hasHeight	**21.50**
hasArea	**190.64**
isConnectTo	**ground**
isVerticalTo	**ground**
isConnectTo	**P1**
isVerticalTo	**P1**
isMeet_Overlap_Meet_Cover_To	**P1**

(2)

Figure 6-12 The individuals transformed from segmentation results with formalized properties

6.6.3 Similarity Evaluation between Transformed Properties or Relations of Individuals and those Defined in Semantic Rules

According to the properties and relations of individual P1, it is an individual of the concept “PlanarPolygon_3D”. Since its height is 3.21, the similarity of properties related to height is calculated by the formula $1-|val-Th|/Th$ (val is the given value, and Th is the defined threshold). The similarity of the property “hasHeight” is 0.8025. Therefore, the similarity vector after the comparison of the properties of

P1 and those defined in the first semantic rule is represented as (1, 1, 1, 0, 1, 1, 1, 0.8025). According to the formula of similarity computation, the similarity between P1 and the first semantic rule is 0.883.

In the similarity evaluation between P1 and the second semantic rule, after the calculation of the distance between “Meet-Overlap-Meet-Cover” in P1 and “Meet-Meet-Meet-Equal” defined in the second semantic rule, their similarity is calculated as 0.875. Finally, the similarity vector of P1 is (1, 1, 1, 1, 0.875,1, 1, 1, 0.8025). After the calculation of similarity, the similarity between P1 and the second semantic rule is 0.997. In conclusion, the second semantic rule is more suitable for inferring the building feature of P1.

6.6.4 Uncertain Reasoning of Building Features in the D-S Framework

For reasoning building features from uncertain information, the properties, relations and some constraints are translated into evidence to support the conclusion of feature recognition. Based on the definition of BPA in the D-S theory, the classification of features is represented as the frame of discernment. Here, the set consisting of the wall, roof, and protrusion is the frame of discernment. Then, the BPA of properties and relations is defined. We defined a table to store the BPA of properties and relations defined in the semantic rules (Table 6-6). The uncertainties of the properties and relations defined in the semantic rules are presented in Table 6-6.

Table 6-6 Basic Probability Assignment (BPA) for properties and relations in semantic rules

Conditions		Building Features			
Properties or Relations	Constraints	Wall	Roof	Protrusion	Wall, Roof
isVerticalTo	ground	0.8	0.1	0.05	0.05
isConnectTo	ground	0.9	0.05	0.05	0
hasArea	greaterThan 4	0.1	0.1	0	0.8
hasArea	lessThan 4	0.2	0.3	0.5	0
hasHeight	greaterThan 4	0.1	0.1	0	0.8
hasHeight	lessThan 4	0.1	0.1	0.4	0.4
Meet-Meet-Meet-Equal	wall	0.4	0.4	0.05	0.15

After the similarity evaluation, the properties and relations defined in the second semantic rule are used to decide on the building feature of P1. Four pieces of evidence are selected for uncertain reasoning in the D-S evidence theory based on the properties and relations in the selected rule. (Table 6-7).

Table 6-7 Selected evidence for concluding on the feature

Evidence	Wall	Roof	Protrusion	Wall, Roof
m_1	0.8	0.1	0.05	0.05
m_2	0.1	0.1	0	0.8
m_3	0.1	0.1	0.4	0.4
m_4	0.4	0.4	0.05	0.15

After reallocating the BPA of evidence using the weight defined by the similarity of properties and relations, the new evidence is updated by the uncertainty of each property and relation (Table 6-8).

Table 6-8 Updated evidence after reallocation by similarity

Evidence	Wall	Roof	Protrusion	Wall, Roof	Wall, Roof, Protrusion
m_1	0.8	0.1	0.05	0.05	0
m_2	0.0802	0.0802	0	0.642	0.198
m_3	0.1	0.1	0.4	0.4	0
m_4	0.35	0.35	0.043	0.131	0.126

Based on the updated evidence, the combination rule is applied to obtain the final results. First, the conflict value K in the evidence should be evaluated to decide whether some evidence conflicts with each other. The value of K between m_1 and m_2 is 0.11. The value of K between m_1 and m_3 is 0.5 and the value between m_1 and m_4 is 0.39. We can conclude that there is no conflicting evidence. Thus, the typical combination rule is used to fuse the evidence. The mass function of combining evidence is shown in Table 6-9. The $m_{12}(*)$ column indicates the mass function after fusing m_1 and m_2. The results in the column $m_{12}(*)$ are used to fuse m_3 continually. Finally, the result of fusing m_1, m_2, m_3 and m_4 is shown in the column $m_{1234}(*)$, which is the final mass function of sets.

Table 6-9 The mass function after combining evidence

Mass	$m_{12}(*)$	$m_{123}(*)$	$m_{1234}(*)$
$m(Wall)$	0.833	0.844	0.846
$m(Roof)$	0.108	0.133	0.136
$m(Protrusion)$	0.0111	0.003	0.0024
$m(Wall, Roof)$	0.0473	0.0196	0.015

After calculating the belief of sets, the support level of building features (wall, roof, and protrusion) is acquired. As shown in Figure 6-13, after fusing the evidence m_1 and m_2, the feature "wall" has the highest belief. When more evidence is combined, the belief of the feature "wall" goes up. When four pieces of evidence are fused, the belief of each feature is finally determined. Following the belief of features, the conclusion of feature recognition for P1 is a wall. In fact, this conclusion is consistent with the real feature type of P1.

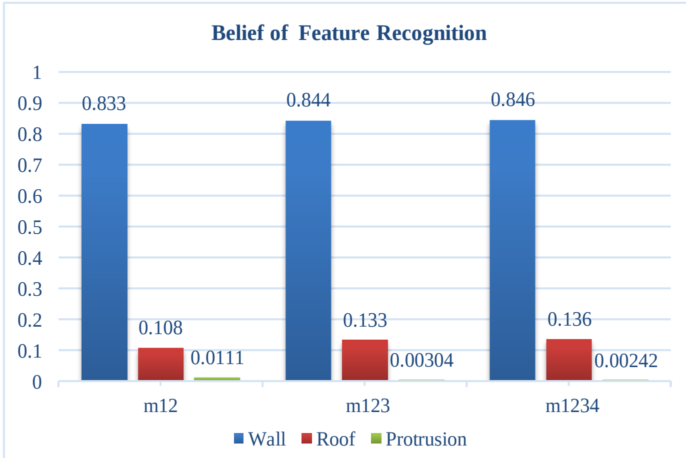


Figure 6-13 Belief of features after fusing evidence

6.6.5 Discussion

In the above experiment, the transformation from segmentation results to individuals with properties and relations in the ontology is conducted using our proposed solution. The similarity evaluation approach between the transformed properties and relations from segmentation results and those predefined in the semantic rules provide ways of comparing the similarity of formalized representation of properties and relations. Then the suitable semantic rule for reasoning building features is selected by similarity evaluation. The properties and relations defined in the selected semantic rule are chosen to reason building features. The proposed solution links the uncertainty of planar segments and the formalized representation of properties and relations in the knowledge base by similarity evaluation. Finally, the uncertainties of properties and relations involve uncertain reasoning of building features in the D-S evidence theory. However, the uncertainty of properties and relations should be predefined as BPA of the sets of features according to experiential knowledge. The definition of uncertainty should be consistent with the common knowledge represented by semantic rules in the knowledge base. Moreover, because the uncertain properties and relations are considered as evidence to reason features, there should be at least two pieces of evidence in the D-S evidence theory.

6.7 Conclusion and Future Work

In this paper, we proposed inferring building features automatically from segmentation results of point clouds based on the prior knowledge of buildings. Some common knowledge is represented as semantic rules in the knowledge base. Due to the uncertain information from segmentation results, three primary steps for automatic uncertain reasoning of building features are proposed: (1) Transform segmentation results into individuals with properties and relations in the ontology. (2) Evaluate the similarity between transformed properties and relations of individuals and those defined in the knowledge base. Based on similarity evaluations, the most suitable semantic rule for uncertain reasoning was selected from the knowledge base. (3) The properties and relations defined in the selected semantic rule are considered as evidence to infer building features using D-S evidence theory from uncertain information.

Our proposed solution for automatic uncertain reasoning of building features introduces the uncertainty of formalized representation of properties and relations of individuals transformed from segmentation results. Meanwhile, the similarity evaluation of formalized representation of properties and relations is used to reassess the uncertainty of properties and relations for reasoning building features in the D-S theory. The advantage of our proposed solution is that it is possible to adjust the predefined uncertainties of properties and relations in the D-S evidence theory framework according to the specifications and knowledge about buildings. In future work, we will focus on extending the uncertain reasoning of feature recognition to more complex urban scenes. Additionally, we will work on automatically defining BPAs of feature sets according to predefined semantic rules and common knowledge. Based on feature recognition, we will explore the use of semantic information of building components to complete 3D geometric models combining the knowledge about buildings.

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CHAPTER 7 Creation of Improved Complete 3D Building Models

7.1 Résumé

La création de modèles de bâtiment 3D complets sur la base d'informations extraites des résultats de segmentation de nuages de points incomplets causés par une occlusion est un problème difficile dans la modélisation 3D automatique à partir de nuages de points LiDAR. La connaissance des composants de bâtiment est utile pour compléter les composants de bâtiment. Les relations topologiques entre un mur et un toit fournissent des informations cruciales pour compléter les parties manquantes dans les murs et les toits, car les connexions possibles entre le mur et le toit peuvent être prédites sur la base des relations topologiques détectées à partir des résultats de la segmentation. Pour évaluer l'exhaustivité des composants du bâtiment, la fonction de coût est proposée en fonction de la définition de l'ordre d'une arête. Ensuite, les parties manquantes dans les composants de bâtiment peuvent être progressivement déduites basé sur la connexion possible prévue et du coût des segments de ligne à l'intérieur de la limite des composants. Les expériences décrites dans le chapitre suivant décrivent les détails de la création de modèles de bâtiment 3D complets, y compris les démonstrations des résultats de la segmentation, les relations topologiques, la détection des limites, le coût des composants du bâtiment et les étapes détaillées nécessaires pour compléter les parties manquantes.

7.2 Abstract

Creating complete 3D building models based on information extracted from segmentation results from incomplete point clouds caused by an occlusion is a challenging issue in automatic 3D modeling from LiDAR point clouds. Knowledge about building components is helpful in completing building components. Topological relations between a wall and a roof provide crucial information for completing the missing parts in walls and roofs because the possible connections between the wall and the roof can be predicted based on the topological relations detected from segmentation results. To evaluate the completeness of building components, the cost function is proposed based on the definition of the order of an edge. Then, based on the predicted possible connection and the cost of the line segments within the boundary of the components, the missing parts in building components can be gradually inferred. The experiments described in the following chapter outlined the details for creating complete 3D building models, including demonstrations of segmentation results, topological

relations, detection of boundaries, the cost of building components and the detailed steps involved in completing missing parts.

7.3 Introduction

3D modeling of urban scenes from LiDAR point clouds is increasing in popularity since a large amount of highly detailed data can be rapidly acquired from the environment being examined. For modeling purposes, segmentation of point clouds allows for the extraction of different components of objects in an urban scene. During segmentation, building components can be broken down into geometric primitives, such as planes, cylinders, etc. The boundaries of geometric primitives determine their geometric shape in 3D spaces. For instance, the boundaries extracted from planar segments determine the final geometric shape of building components (triangles, rectangles, squares, circles, and other polygons). Building components represented by geometric primitives and their boundaries are primary information carriers of topological relationships and semantic annotations for creating geometric 3D Boundary Representation (B-Rep) building models. Due to incomplete point clouds caused by occlusions in scanned urban scenes, segmentation results of object components produced by shape-based segmentation algorithms can be incomplete as well. Based on these segmentation results, the quality of the extracted geometric shapes of building components and their topological relations are not as perfect as they are in the real world. To determine topological relations between components, one must also know the boundaries. However, incomplete building components can generate uncertain boundaries and topological relations, which affects the quality of geometric models. Consequently, creating complete geometric 3D models from incomplete components with uncertain boundaries and topological relations is a challenging task due to the missing parts in the point clouds.

7.4 Roles of Knowledge in the Extraction and Modeling of Building Components

Information related to geometric and topological relations is essential for feature recognition (e.g., walls and floors of a building). The type of information that can be extracted from point clouds includes geometric information about building components (geometric shape, parameters for representing the geometry equation, length, height, width, area and the boundaries of geometries), geometric relations between building components (parallel, orthogonal, intersect, and coplanar) and topological relations between components. Parameters for representing the geometric primitives can be extracted from shape-based segmentation algorithms. Geometric relations rely on the equation parameters representing the segmented geometric primitives from point clouds. Geometric relations between building components can then be determined based on these equations. Based on the shape and boundaries of geometric primitives, topological relationships between components can be obtained according to our proposed models for topological relationships among object components (Xing, 2018; Xing, 2016b). The information mentioned above provides the basis for extracting the semantics of object components with the help of a knowledge base that describes an urban scene and objects in detail. In the knowledge base, the knowledge for recognizing the semantics of building components is represented and formalized as predefined rules. Hence, the semantics of building components can be obtained through semantic reasoning based on the extracted information on specific object components. Therefore, knowledge plays a vital role in the reasoning of the semantic labels of building components from segmentation results.

Building component semantics are promising for providing more information to determine precise topologies between building components and for predicting the boundaries of incomplete parts. A part of the semantics of buildings components is recognized from the results of the segmentation of buildings, based on their geometric information, geometric relations, and topological relations. When the semantics of building components are known, the topological relations between building components defined in the knowledge base are helpful in validating and correcting the topological relations between components extracted from point clouds. However, it is still difficult to complete the missing parts based on some predefined semantic rules because the missing parts of the components caused by occlusion are unpredictable. To be certain, the semantics of building components are required in order to successfully complete geometric 3D models.

Knowledge of buildings can be used to improve the completeness of geometric models when the building components and their semantics are known. The semantic information also includes constraints on components and their relations. These constraints might provide some clues in determining the final geometric shapes of the components using possible geometric and topological relations. The definition of constraints is closely related to the level of details (LODs) of 3D models of buildings. Since the point clouds of an urban scene acquired by mobile terrestrial LiDAR scanners only record the outer surface of objects, building components recorded in point clouds include walls, roofs, windows, and doors. Based on terrestrial and airborne LiDAR point clouds, geometric 3D building models with LOD 3 can be created (Böhm, 2005; Kedzierski, 2014). The definitions for LOD 2 and LOD 3 from the OGC CityGML specification document are presented below (Consortium, 2012).

- LOD 2: building model has differentiated roof structures and thematically differentiated boundary surfaces.
- LOD 3: architectural models with detailed wall and roof structures potentially including doors and windows. It is mostly used for landmarks.

In LOD3, doors and windows are potentially included based on the details presented in LOD 2. However, missing parts in LiDAR point clouds caused by occlusions lead to the challenge of creating a complete geometric model of a building with LOD 3. Since windows and doors are generally on the walls, missing parts in a terrestrial LiDAR point cloud of a wall can cause incompleteness in data, particularly when windows and doors also need to be extracted. To create complete geometric building models, it is first necessary to check the completeness of LOD 2 models. Knowledge about building components (i.e. roofs and walls) is helpful in improving the completeness of LOD 2 building models. However, common knowledge about building components at LOD 2 shown in Figure 7-1 is not enough to complete the missing parts of point clouds due to various occlusion. For instance, the topological relations between walls and roofs do not only include “connect” and “above” relations represented in the model proposed by (Nüchter, 2008). Knowledge about building components should be clearly formalized and refined in order to represent the possible connections between components.

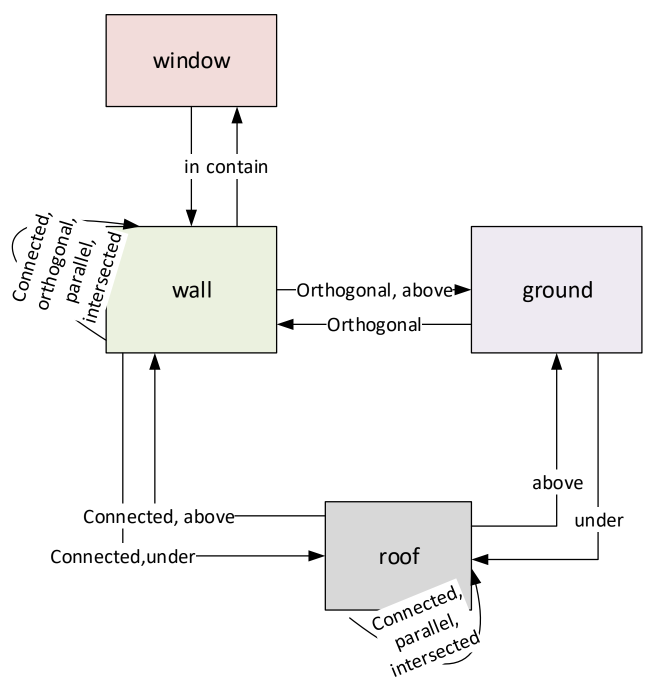
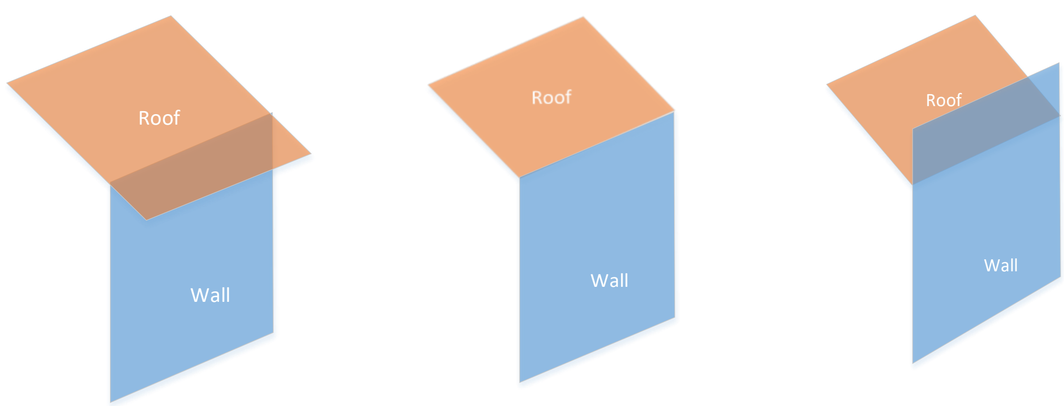


Figure 7-1 Common constraints for building components (Nüchter, 2008)

7.5 Proposed Solution for Completing Wall-Roof Connections in LOD 2 Building Models

7.5.1 Spatial Connections between Walls and Roofs

The topological relations between roofs and walls are crucial for completing the missing parts of LOD 2 building models. Here we list five possible topological relations between walls and roofs based on our proposed models for topological relationships in (Xing, 2018) among object components. When the roof is over the wall, the top of the wall is located on the intersection line between the roof and the wall. The relation between the intersection line and the roof plane is “overlap” (Figure 7-2 (A)). A second example is when the intersection line between the wall and the roof is on the boundary of the wall and the roof. In this case, their topological relation is “meet” (Figure 7-2(B)). The third example is when the topological relation between the wall and the intersection line of the wall and the roof is “overlap and outside” and the top of the wall is higher than the intersection line (Figure 7-2 (C)). Similarly, the roof could be located outside the wall and connect to the wall (Figure 7-2 (D)), or the wall and the roof could intersect each other (Figure 7-2(E)). According to the knowledge of spatial connection relations among building components, the missing parts of the components can be completed by the constraints between components predefined by the possible topological relations between roofs and walls. Therefore, the constraints defined for each example are considered as knowledge about LOD 2 building models based on topological relations between roofs and walls extracted from point clouds.



(A) Roof “over” wall

(B) Roof “meet” wall

(C) Wall top “over and outside” roof

(D) Wall top"over and inside" roof

(E) Roof "intersect" wall

Figure 7-2 Examples of spatial connection relations between a wall and a roof

7.5.2 Framework for Creating Complete Building Models from Incomplete Point Clouds

Due to the occlusion problems, it is sometimes difficult to determine the spatial relations between components of a building in a point cloud. In such situations, the knowledge of building components is crucial for aggregating planar segments and defining the spatial relations between components such as roofs and walls. As presented in Figure 7-3, the knowledge base defines the link between the detected relations between building components from point clouds and the possible spatial relations between them, deduced from the common knowledge about them. Although the knowledge base provides a possible reference for spatial connections between building components, a final decision on their connections still requires geometric information about the components. Therefore, the steps involved in completing building components are as follows:

Step 1: Identify the topological relations between planar segments based on the segmentation results.

Step 2: Recognize the semantics of building components and attach labels to them (e.g., walls, roofs, etc.).

Step 3: Enquire about the possible spatial connections among building components from the knowledge base (Table 7-1).

Step 4: Identify the completeness of building components, such as walls and roofs.

- **Step 4.1:** Define the cost function of the line segments for evaluating the completeness of building components. Components with a high cost represent a high degree of incompleteness.
- **Step 4.2:** Select the components that need to be identified to complete the building model. The

intersection lines are used as the constraints for determining the missing part.

Step 4.3: After each iteration, when the sum of the cost of the components stays stable, the missing parts of building components are restored (as shown in the last step of Figure 7-3).

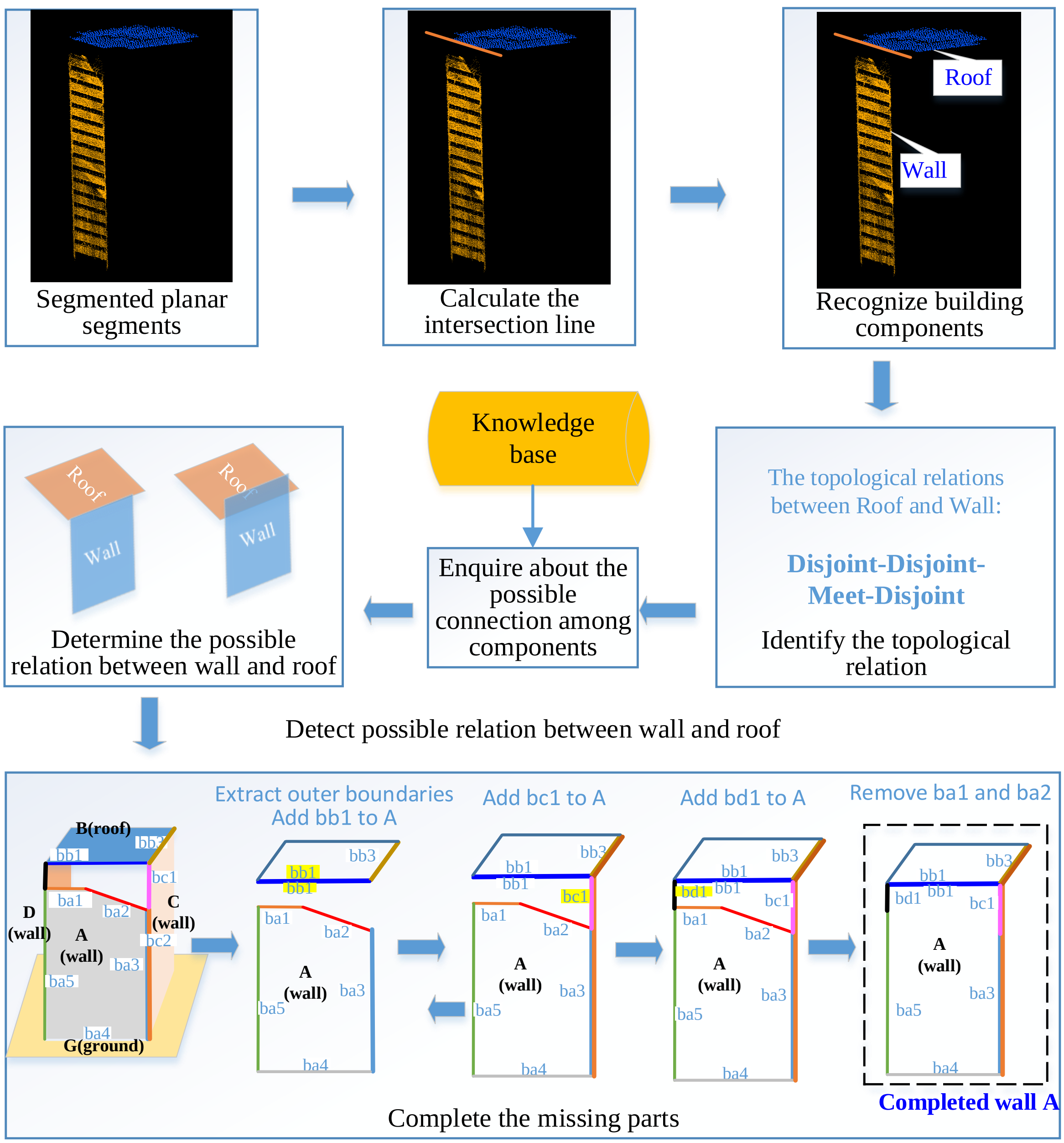


Figure 7-3 Proposed framework for creating complete building models from incomplete point clouds

Table 7-1 Link between detected topological relations and the possible spatial connection between a roof and a wall in the knowledge base (* indicates topological relations)

Topological relations between roof and wall identified from point cloud	The possible spatial connection between roof and wall in the knowledge base
Disjoint-Disjoint-Meet-* Disjoint-Meet-Disjoint-* Meet-Meet-Meet-*	Roof “meet” wall (Figure 7-2 (B))
Intersect-Overlap-Meet-* Intersect-Meet-Overlap-* Disjoint-Overlap-Disjoint-* Disjoint-Disjoint-Overlap-*	Roof “over” wall, Wall top “over and outside” roof, Wall top “over and inside” roof (Figure 7-2 (A), (C) and (D))
Intersect-Overlap-Overlap-*	Roof “intersect” wall (Figure 7-2 (E))

7.5.2.1 Definition of the Completeness of Components

The intersection lines between building components represent significant information for completing components that have missing parts because the relations between the intersection line and the components can be used to predict the spatial connections between components. In addition, due to the diversity of the missing parts of the components and the limited references predefined in the knowledge base, the components should be completed according to their geometric information, as well as their neighbors’ knowledge. For this purpose, we first need to ascertain whether a given component is complete. If it is not complete, we then need to decide what information can be used to complete the component. For a complete 3D geometric model, we can use the definition of “the order of an edge” to help decide on the completeness of a component. Here, an edge is represented as a line segment of a boundary of a component.

The order of an edge: the order of an edge is defined as the number of facets sharing an edge. O_{bi} represents the order of the edge bi .

In a manifold mesh, every edge is shared by at most two facets (Figure 7-4(A) and (C)). For example, the edge l_{ab} is shared by two facets in Figure 7-4(A). Similarly, in a complete B-Rep 3D geometric model, an edge is shared by at least two facets (Figure 7-4(D)). The order of edge l in (Figure 7-4(B)) is 3.

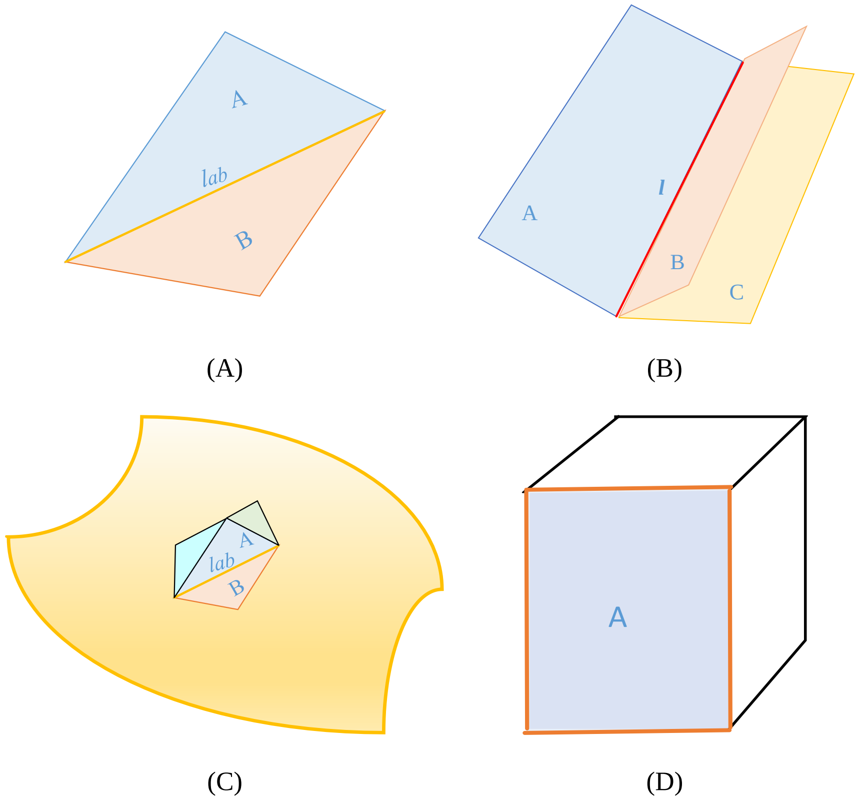


Figure 7-4 Illustrations of the order of edges: (A) The order of *lab* is 2; (B) The order of *l* is 3; (C) The order of edges in a manifold mesh; (D) The order of edges in a complete 3D geometric model

Based on the above definition and illustrations, judgment on a complete component depends on the order of edges in the boundary of the component because each edge should be shared by two components in a complete building geometric model. In addition, the principles of completing 3D geometric models from point clouds are also crucial. Here we outline principles for complete building components from incomplete point clouds based on knowledge about building components and geometric information of components, geometric and topological relations between components.

(1) The calculated intersection lines between the neighboring components should be shared by at least two components. The topological relations between the intersection line and the components on a 3D plane should "meet" or "overlap" in a completed geometric model.
(2) The minimum area should be used to complete the missing parts of the components;
(3) The missing parts should be completed based on the geometric information of components and their neighbors.

Several examples are presented below to show the steps involved in completing building components. For the example shown in Figure 7-5, the relation between the intersecting line and the roof is "meet."

The relation between the intersecting line and wall-16 is "disjoint." Then, we can enquire about the possible connections between the wall and roof as shown in Figure 7-2 (B) and (C). After extracting the outer boundaries of components and comparing the top of the wall and roof, the connection between the wall and roof can be deduced as shown in Figure 7-2 (B). However, it is insufficient to complete the missing part of the wall because the predefined connections among building components are limited and the information about the neighboring components is also required to complete the missing parts. For instance, in Figure 7-6 (A), the outer boundaries of components A and B are extracted, and the topological relation between them is "Meet-Meet-Meet-Meet." It is impossible to know whether it is complete or where the incomplete parts are based on the identified topological relations. According to the references for spatial connections between roofs and walls (as shown in Figure 7-6 (B)), components A and B are completed as shown in Figure 7-6 (C). In fact, the real connections between components are presented in Figure 7-6 (D). This particular example reveals that it is difficult to restore the missing parts if there is no neighbor knowledge due to additional missing components. Component A has a missing part while component B is complete. Therefore, the process of completing building components requires a flexible method to identify the missing parts and complete them according to the geometric information and the topological relations of components and their neighboring components.

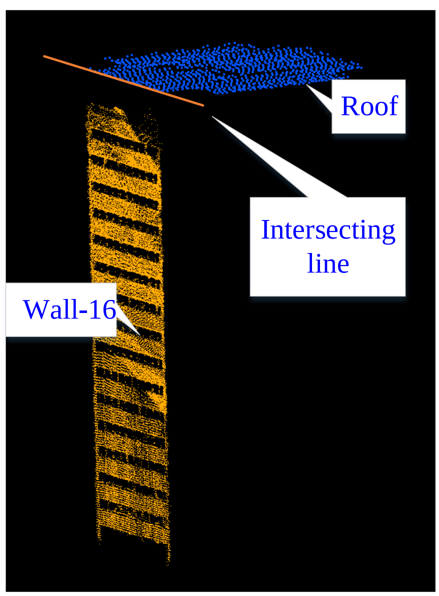
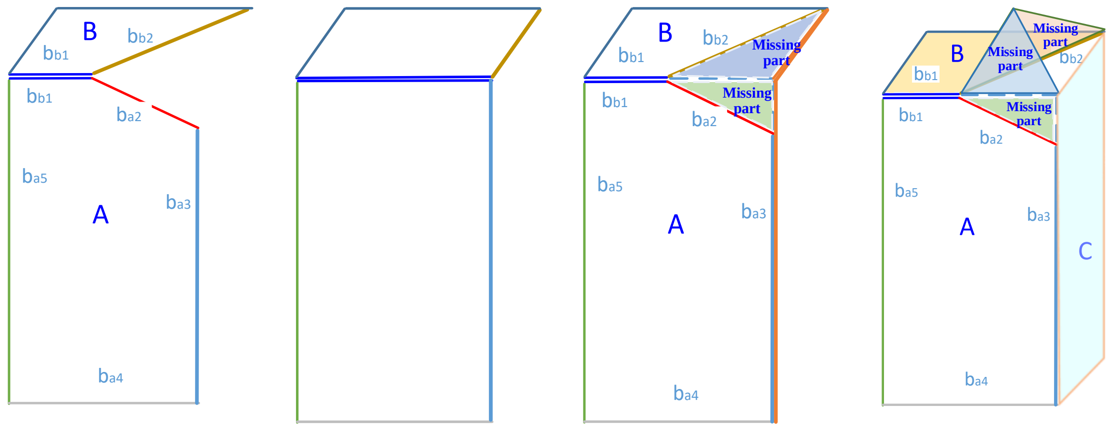


Figure 7-5 Example of an incomplete wall segmented from point clouds



(A) (B) (C) (D)

Figure 7-6 (A) Detected outer boundaries; (B) Reference for spatial connection in the knowledge base; (C) Predicted missing part after completion; (D) Example of connections between components in reality

To evaluate the completeness of a building component, we can define the cost function of a planar segment that consists of the cost of the line segment to represent the boundaries of components. The cost function is defined below and several examples are given to explain the steps involved in completing building components.

7.5.2.2 Definition of the Cost Function

For a component represented by a planar segment, its boundary composed of polygons contains several line segments. Here, we use the term "planar segment" or "planar region" to represent a component. The cost of a planar segment (c_p) is defined as:

$$c_p = \sum_{i=1}^{N} c_{bi} \qquad \textbf{(Eq 7-1)}$$

Where c_{bi} is the cost of the line segments *bi.*

The cost of a line segment (c_{bi}) is defined as:

$$c_{bi} = k_1\delta_1 + k_2 O_{bi} \qquad \textbf{(Eq 7-2)}$$

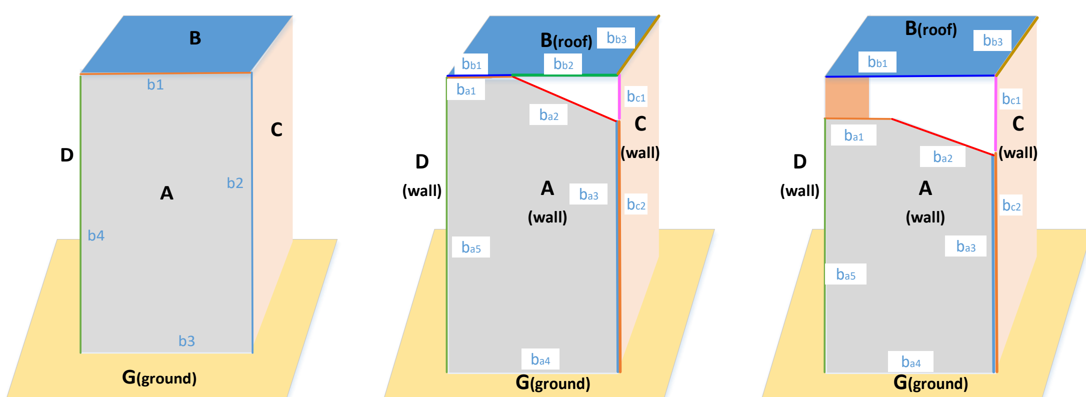
The definition of the parameters in the cost function is presented in Table 7-2. Here, parameter values are defined to distinguish the location relations between boundary line segments and the calculated intersection line. In the cost function of a line segment, δ_1 is defined to distinguish whether or not the line segments are on the intersection lines. When a line segment is on the intersection line, δ_1 should be given a small value. When a line segment is on the intersection line, its cost is less than the cost of a line segment that is not on the intersection line. O_{bi} is the value of the order of a line segment. k_1 is the factor of δ_1 and k_2 is the factor of O_{bi}. Thus, a line segment shared by two components on the intersection line has the minimum cost value of 1. Line segments on the intersection line but not shared by other components and line segments that are not on the intersection line have higher cost values.

Table 7-2 Definition of cost function parameters

The location of bi	k_1	δ_1	O_{bi}	k_2	Cost
Line segment (bi) of boundaries on the intersection line	1	1	$O_{bi}=1$	5	6
			$O_{bi}>1$	0	1
Line segment (bi) of boundaries not on the intersection line	10	2	$O_{bi}=1$	10	30

According to the definition of parameters, the cost values for the various line segments representing boundaries are given as follows:

- When a line segment is on the intersection line and its order is equal or greater than 2, the cost is 1.
- When a line segment is on the intersection line and its order is 1, its cost is 6;
- When a line segment is not on the intersection line, its cost is 30.



(A) (B) (C)

Figure 7-7 Calculating the cost of planar segments. (A) Complete building model; (B) Example of the planar segment A with missing parts; (C) Another example of planar segment A with missing parts

Based on the above information on the cost of line segments, we can surmise that incomplete components have a greater cost value than complete components. If the boundary of a complete component consists of *m* line segments, the cost value of this component is *m*. Similarly, if the boundary of a component contains *m* line segments and its cost value is greater than *m*, we can conclude that this component is not complete. Some examples are given below to explain the process of calculating the cost of components (Table 7-3). According to the comparison between the costs of planar segment A, the cost of the planar segment A in Figure 7-7(C) is greater than the cost of planar segment A shown in Figure 7-7 (B). Similarly, the sum of the costs of all components in an incomplete geometric model is higher than in a complete geometric model. Therefore, the proposed cost function is effective in evaluating the degree of completeness of a component evaluated by the sum of the cost values of line segments representing a boundary.

Table 7-3 Details for calculating the cost of planar segments

Figure	Components		Topological relations	Cost of components	Sum of cost
Figure 7-7(A)	A	B	Meet-Meet-Meet-Equal	$C_{pA} = 4$	16
	A	C	Meet-Meet-Meet-Equal	$C_{pB} = 4$	
	A	D	Meet-Meet-Meet-Equal	$C_{pC} = 4$	
	A	G	Meet-Meet-Meet-Equal	$C_{pD} = 4$	
Figure 7-7(B)	A	B	Meet-Meet-Meet-Cover	$C_{pA} = 34$	58
	A	C	Meet-Meet-Meet-Cover	$C_{pB} = 10$	
	A	D	Meet-Meet-Meet-Equal	$C_{pC} = 10$	
	A	G	Meet-Meet-Meet-Equal	$C_{pD} = 4$	
Figure 7-7(C)	A	B	Disjoint-Disjoint-Meet-Disjoint	$C_{pA} = 63$	92
	A	C	Meet-Meet-Meet-Cover	$C_{pB} = 9$	
	A	D	Meet-Meet-Meet- Cover	$C_{pC} = 10$	
	A	G	Meet-Meet-Meet-Equal	$C_{pD} = 10$	

7.5.3 Heuristic Completion of 3D Building Models

The problem with completing 3D geometric models is minimizing the cost of all the components of a building. To complete all the components, the process is divided into sequential sub-steps. Essentially, the completion of 3D models is a graph correction problem because the cost of components is closely related to the topological relations between the components of a building. The topologies of components can be represented as a graph and the nodes are components. Inspired by the work of correcting erroneous roof topologies (Xiong, 2014), the graph correction problem can be viewed as an energy optimization problem. After the correction, the target topology graph is the one that minimizes the energy. As for the problem of completing components of a building, the target topology graph of a building has the minimum cost. Since the topological graph with incomplete components maintains a high-energy state, the aim of the process of completing the missing parts is to seek a sequence of changing topology graph S_k to make sure the final output graph (G_{out}) having the minimum cost G_i is the graph obtained during one step of the completion process of completion.

$$G_{out} = \arg\min \sum_{j=1}^{M} C_{pj} \quad \textbf{(Eq 7-3)}$$

$$G_i = S_k G_{i-1} \quad \textbf{(Eq 7-4)}$$

$$S_k = \{S_{k1}, S_{k2,}\ ......, S_{kn,}\} \quad \textbf{(Eq 7-5)}$$

The transition of the topological graph could have many possible sequences to reach a stable energy state. The objective of completing 3D geometric models is to minimize the steps involved in modifying the graph with the smallest cost. To achieve this, we first choose the components that had a smaller cost. Then, the components with a higher cost were selected because the smaller cost components have smaller missing parts and a greater possibility of being completed with less cost. In the following three examples, we demonstrate the detailed steps of completing the missing parts of building components.

7.5.3.1 The Completion Steps: Example 1

For the example shown in Figure 7-7(B), we first calculated the cost of all the components represented by planar segments and sorted them by the calculated cost. Then, the planar segment with the minimum cost was selected. Following verification, the cost of planar segment D is identified as the minimum cost and it is complete. Then, once the planar segments are sorted by their cost, we use the same method to check all the planar segments. The detailed steps are listed below:

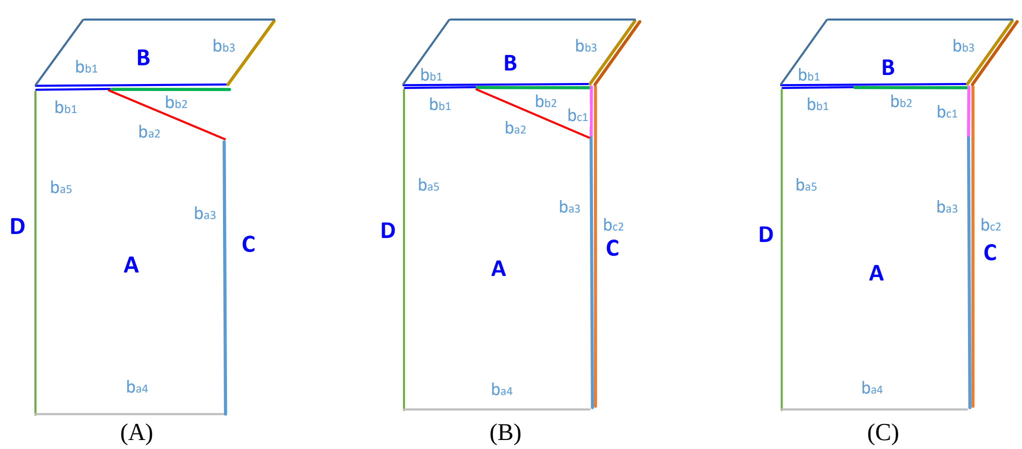


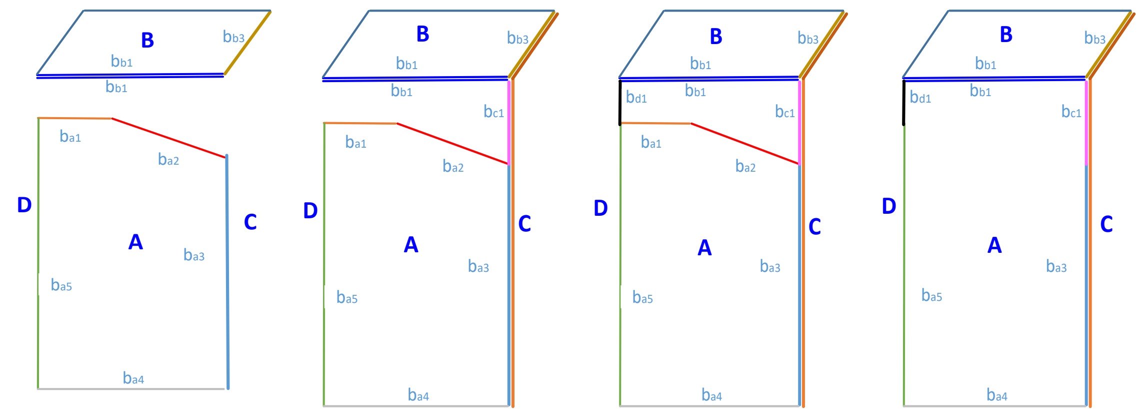
Figure 7-8 Steps involved in the heuristic completion process. (A) add b_{b2} into A; (B) add b_{c1} into A; (C) remove b_{a2} from A

1) Identify the cost of planar segment D. It is 4, which indicates that it is complete.
2) Check the planar segment with the second minimum cost. The cost of planar segments B and C is 10. We then chose component B. The topological relation between planar segment A and B is "Meet-Meet-Meet-Cover" and the line segment of boundaries with the higher cost in planar segment B is on the intersection line. To decrease the cost of planar segment B, we add b_{b2} into the boundaries of planar segment A. Consequently, the cost of B is stable and the cost of A decreases (Figure 7-8 (A)).
3) Repeat the same step to check planar segment C (Figure 7-8 (B)). The line segment b_{c1} is added into the boundaries of planar segment A.
4) Check the boundaries of planar segment A. Since the line segment b_{a2} is located in the polygon and is composed of new boundaries, this line segment should be removed from the current boundaries (Figure 7-8(C)).
5) Finally, the high cost of planar segment A caused by the missing part is in a final stable state and the sum of the cost of all planar segments is stable.

7.5.3.2 The Completion Steps: Example 2

For the example shown in Figure 7-7(C), there is an incomplete planar segment A that does not connect to planar segment B. The steps involved in completing the missing part are shown as follows:

1) Calculate the cost of planar segments.
2) Sort the planar segments by their cost and start to process the segments by minimum cost value.
3) First, check planar segment B. The line segment b_{b1} is added into the boundaries of planar segment A (Figure 7-9(A)). After this step, the cost of planar segment B decreases to 4.
4) Then, check planar segments C and D; similarly, the line segment b_{c1} and b_{d1} are added into the boundaries of planar segment A (Figure 7-9 (B) and (C)).
5) Finally, update the boundaries of planar segments. The final boundaries of planar segment A are determined as shown in Figure 7-9 (D).



(A) (B) (C) (D)

Figure 7-9 Steps involved of heuristic completion. (A) Add b_{b1} into A; (B) Add b_{c1} into A; (C) Add b_{d1} into A; (D) Remove b_{a1} and b_{a2} from A

7.5.3.3 The Completion Steps: Example 3

We present another example of a topological relation between a wall and a roof (Figure 7-10 (A)). In this case, the top of planar segment A (wall) is higher than the top of planar segment B (roof) and the wall is incomplete. The topological relation between planar segments A and B is "Intersect-Overlap-Meet-Cover."

1) Calculate the cost of planar segments.
2) Sort planar segments by their cost.
3) Check planar segment D, and whether it is complete.
4) After checking the cost of each planar segment B and C, the line segments b_{b1} and b_{c1} on the intersection line are added to planar segment A (Figure 7-10 (B)).
5) Check the line segments of boundaries of planar segment A. If the newly added line segments are on the intersection line, we keep them (e.g., line segment b_{a1}.) If the line segment is in the interior of planar segment A and its order is 1, it should be removed from the current boundaries of planar segment A, such as line segments b_{a2} and b_{a3}. Finally, planar segment A is completed and the final boundaries are shown in Figure 7-10(C).

After comparing the three examples, we note that the proposed heuristic method for completing building components can be used to create complete 3D building models. In the proposed method, the topological relations between components and intersection lines are crucial information. Moreover, the criterion of evaluating the completeness of a component is defined by the cost function, which is effective in evaluating the completeness based on the geometric information extracted from point clouds to improve the completeness of a LOD 2 building model.

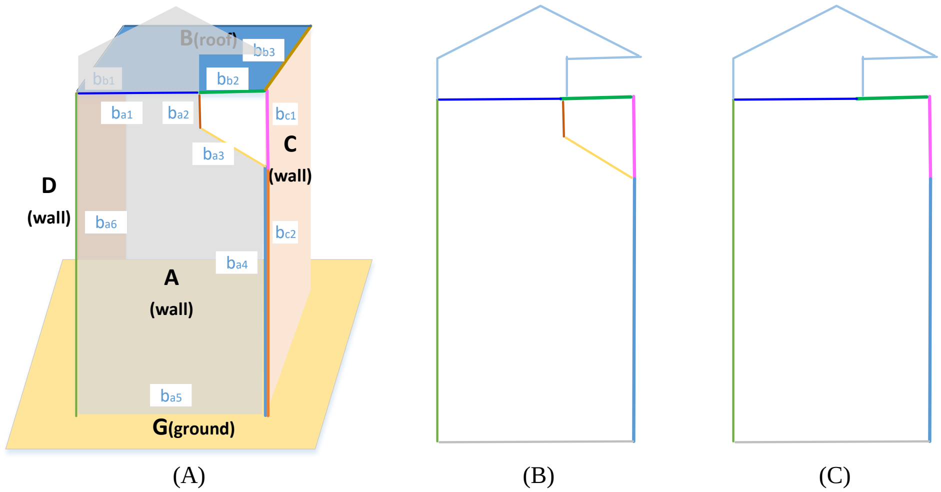


Figure 7-10 Steps for completing the 3D model. (A) Example of incomplete building components; (B) Add b_{b2} and b_{c1} into A; (C) Remove b_{a2} and b_{a3} from A;

7.6 Experiments on Completing Building Components

To implement the proposed method, the following steps are fundamental: segmentation, identifying topological relations between components, detecting the intersection lines, extracting the semantic meanings of components and extracting the outer boundaries. The point clouds in these experiments come from airborne LiDAR point clouds containing roof structures and mobile terrestrial LiDAR point clouds that record details from urban scenes.

7.6.1 Segmentation of Building Components

Building component segmentation results are the source of geometric information about the components. Based on the work presented in the previous chapters, segmentation, the extraction of topological relations, and the extraction of semantic features provide the necessary information about building components. For example, the Google Earth image clearly shows the structure of a building (Figure 7-11 (A)). In Figure 7-11 (B), the point cloud obtained using mobile LiDAR did not capture the complete building structures, and the wall structure is far from perfect. The segmentation results of the point cloud are shown in Figure 7-11 (C) and (D). Based on the segmentation results, we can see that the main structures of this building are segmented using our proposed segmentation algorithms.

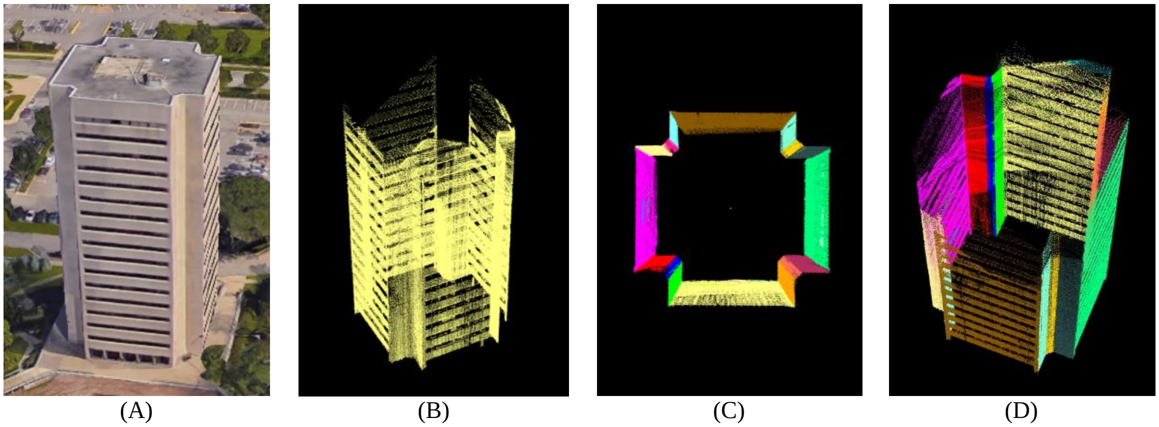


Figure 7-11 Segmentation of a building. (A) Image of the building; (B) Point cloud of the building; (C) Segmentation results of the building (top view); (D) Segmentation results of the building (another view).

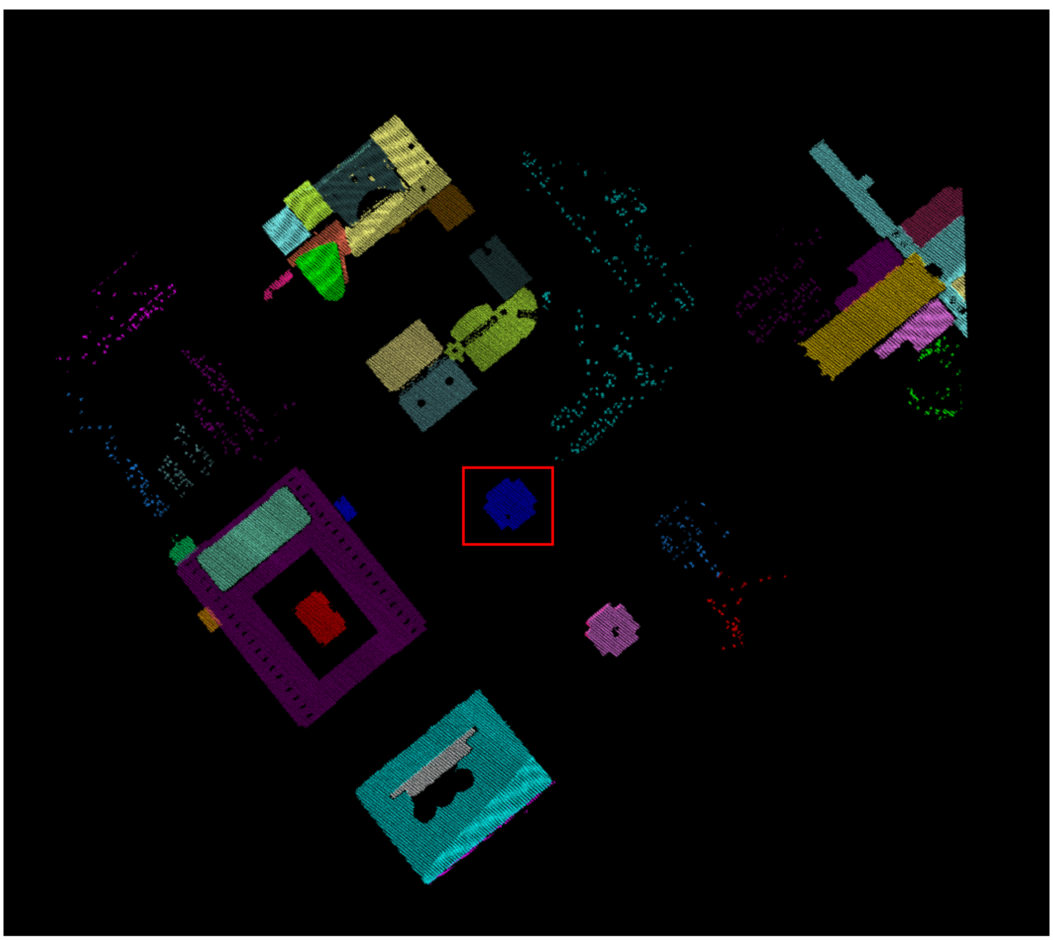
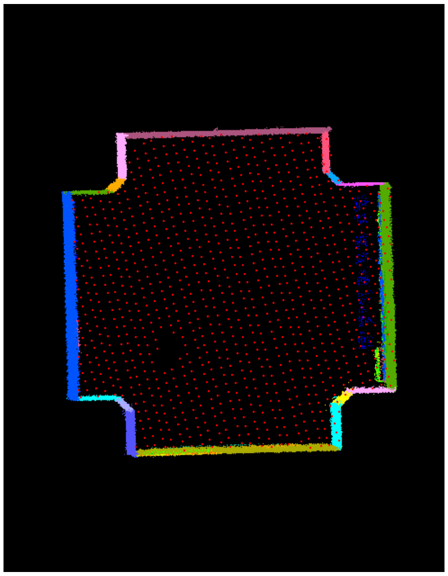
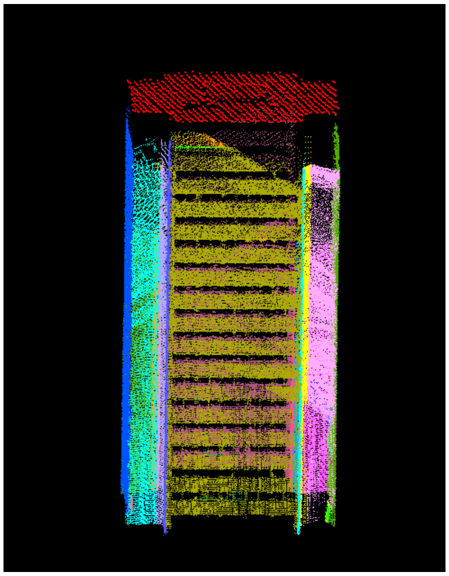


Figure 7-12 Segmentation results of roof structures. The roof of the building being studied is shown in the red rectangle

Roof structures of buildings are crucial for reconstructing whole building structures to determine the shape of walls and to create complete LOD 2 3D geometric building models. In Figure 7-12, we choose a part of the airborne LiDAR dataset that contained the roof structure of the building shown in Figure 7-11 (blue part). Figure 7-13 presents the building from top and side views using point clouds. Based on the segmented point cloud of the building, we can see that the tops of walls do not connect to the roof because of missing parts in the walls. There are 29 planar segments in Figure 7-13.



(A)



(B)

Figure 7-13 Segmentation results of the integration of airborne and terrestrial point clouds. (A) Top view; (B) Side view

7.6.2 Identification of Topological Relations

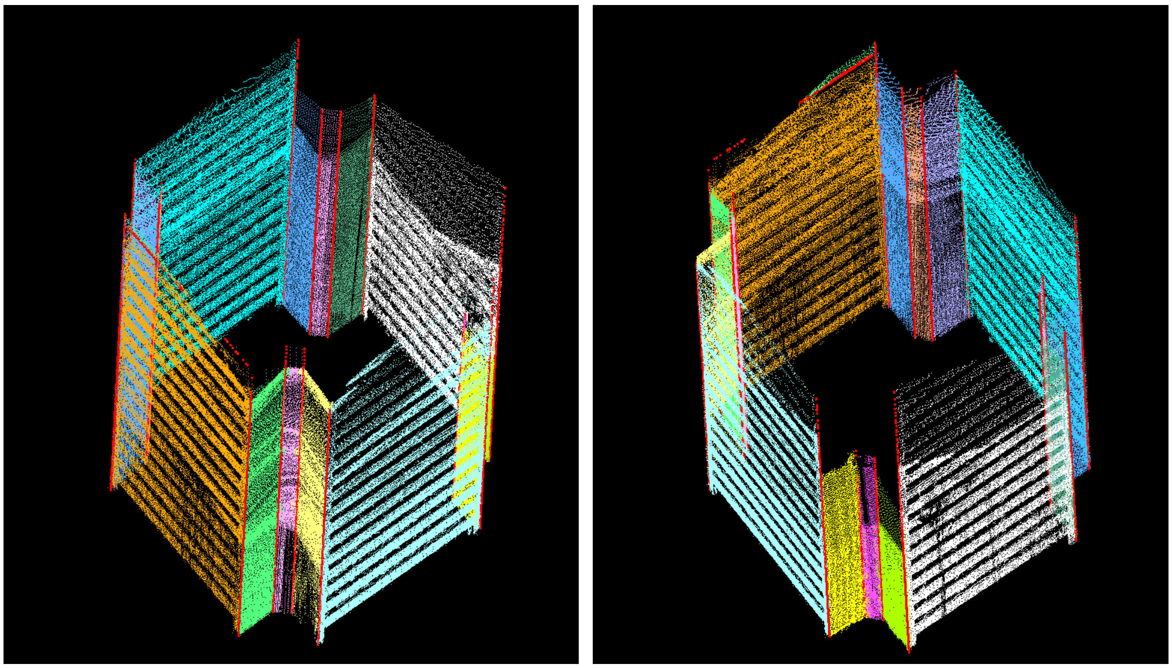
Following the segmentation process, the components of buildings are represented as planar segments. The topological relations among components are also crucial for extracting the semantic meaning of the components. Mobile LiDAR datasets mainly contain wall structures of buildings. Therefore, we first need to identify the possible walls from the segmentation results. Based on the knowledge about building walls, any opaque part of the external envelope of a building that is at an angle of 70° or more to the horizontal is considered a wall (Ltd, 2017). The angle between planar segments and the horizon is defined as 70° or greater to extract all possible wall structures from point clouds.

Based on the segmentation results, the geometric properties of the components, the geometric relations and the topological relations among them can be extracted. In Table 7-4, we present the topological relations among the possible walls of the building. These topological relations among planar segments are identified based on our proposed topological model for representing the topological relations between the components of 3D objects with complex structures (Xing, 2016b). Additionally, the intersecting lines among the neighboring components are obtained (Figure 7-14) and these intersection lines are necessary for determining the precise boundaries of the components.

Table 7-4 Topological relations between components (pr = planar region)

Assigned name of components	Neighboring components	Topological relations
pr 10	pr 9	Intersect-Meet-Overlap-Cover
	pr 11	Intersect-Meet-Overlap-Overlap
pr 9	pr 8	Intersect-Overlap-Meet-Overlap
	pr 10	Intersect-Overlap-Meet- Cover
pr 8	pr 7	Intersect-Meet-Overlap-Cover
	pr 9	Intersect-Meet-Overlap- Overlap
pr 7	pr 6	Meet-Meet-Meet-Overlap
	pr 8	Intersect-Overlap-Meet- Cover
pr 6	pr 5	Intersect-Meet-Overlap-Cover
	pr 7	Meet-Meet-Meet-Overlap
pr 5	pr 4	Intersect-Meet-Overlap-Cover
	pr 6	Intersect-Overlap-Meet-Cover
pr 4	pr 3	Intersect-Overlap-Meet-Contain
	pr 5	Intersect-Overlap-Meet-Cover
pr 3	pr 2	Intersect-Overlap-Meet-Overlap
	pr 4	Intersect-Meet-Overlap-Contain
pr 2	pr 1	Intersect-Meet-Overlap-Cover
	pr 3	Intersect-Meet-Overlap-Overlap
pr 1	pr 17	Intersect-Overlap-Meet-Overlap
	pr 16	Intersect-Overlap-Meet-Contain
	pr 2	Intersect-Overlap-Meet-Cover
pr 17	pr 18	Intersect-Overlap-Meet-Cover
	pr 1	Intersect-Meet-Overlap- Overlap
pr 16	pr 1	Intersect-Meet-Overlap-Contain
	pr 18	Meet-Meet-Meet-Disjoint
	pr 15	Intersect-Meet-Overlap-Overlap
pr 18	pr 17	Intersect-Meet-Overlap-Cover
	pr 16	Meet-Meet-Meet-Disjoint
pr 15	pr 14	Intersect-Overlap-Meet-Overlap
	pr 16	Intersect-Overlap-Meet-Overlap
pr 14	pr 15	Intersect-Meet-Overlap-Overlap
	pr 13	Intersect-Meet-Overlap-Cover
pr 13	pr 12	Intersect-Overlap-Overlap-Overlap
	pr 14	Intersect-Overlap-Meet-Cover
pr 12	pr 11	Intersect-Overlap-Meet-Contain
	pr 13	Intersect-Overlap-Overlap-Overlap
pr 11	pr 12	Intersect-Meet-Overlap-Contain
	pr 10	Intersect-Overlap-Meet-Overlap

The graph structure is used to store topological relations among building components. The nodes represent building components and the edges represent the topological relations between the nodes. When necessary, the graph can be used to search for topological relations.



(A) (B)

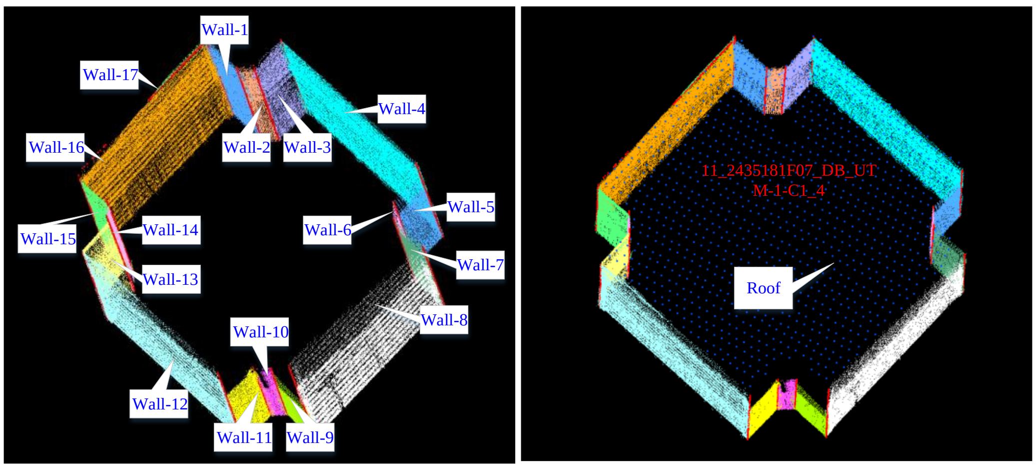
Figure 7-14 Segmentation results of the building and intersection lines. (A) View 1; (B) View 2

7.6.3 Extraction of Semantic of Building Components

When the geometric information about the components, the geometric relations between components and their topological relations are known, they can be transformed into properties of individuals, and the relations among them in the knowledge base. Then, semantic reasoning is conducted based on the reasoner and semantic rules. After the reasoning process, the semantic meanings of the building components are inferred using the predefined semantic rules. For components that cannot be reasoned by predefined rules, the proposed methods for feature recognition from uncertain segmentation results of the building are used. After feature recognition, 18 planar segments are recognized as walls and roofs, as shown in Table 7-5 and Figure 7-15. In Figure 7-15 (A), the semantic meanings of the components are attached to planar segments with assigned names (e.g. wall-1 is the semantic annotation of planar region 1 (pr 1).

Table 7-5 The components and their semantic meanings

Assigned name	Semantic feature
pr 1, pr 2, pr 3, pr 4, pr 5, pr 6, pr 7, pr 8, pr 9, pr 10, pr 11, pr 12, pr 13, pr 14, pr 15, pr 16, pr 17	wall
11_2435181F07_DB_UTM-1-C1_4 (the name given to a segment)	roof



(A) (B)

Figure 7-15 Semantic features of the building. (A) Walls; (B) Roofs

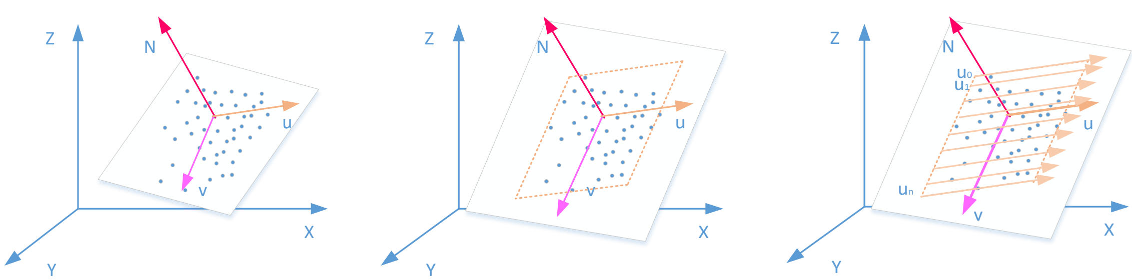
7.6.4 Implementation of the Process for Completing 3D Geometric Models from Building Components

The pivotal step in implementing the heuristic method of completing 3D geometric models is to distinguish the outer boundaries of the building components. These boundaries are classified into outer and inner boundaries. The outer boundaries express the geometric shape of the building components and determine the topological relations of the components. The inner boundaries could represent other components, such as windows and doors within the walls.

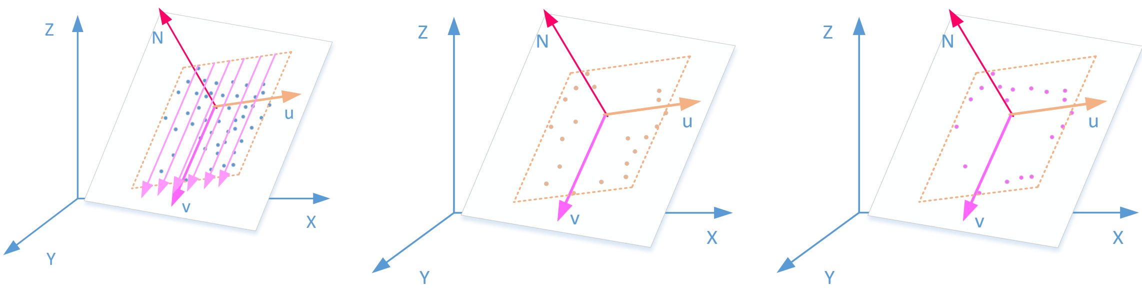
There are two ways to extract the boundaries of a planar segment: extraction of the convex hull and the concave hull. The convex hull contains all the points of a planar segment in the smallest convex set. However, if the point density of the planar segment is uneven, the convex hull cannot represent accurate boundaries. Using the concave hull to represent boundaries of geometric shapes is preferable because it is more efficient in extracting boundaries in detail. The method of extracting the concave hull based on the alpha shapes algorithm (Wei, 2008) and the method based on the angle criterion for identifying points on boundaries (Sampath, 2007) (Rusu, 2011) can be used to extract the boundaries of planar segments from point clouds. However, the limitation of the alpha shapes algorithm is that it cannot distinguish outer and inner boundaries. The algorithm in (Sampath, 2007) cannot extract good quality boundaries from point clouds with uneven density because this method depends on the selection of neighbors. This method does work well, however, with point clouds of uniform density. The solution is robust in identifying boundary points but it cannot directly extract outer boundaries. In our proposed method of completing 3D geometric models, the outer boundaries are crucial for computing the cost of each component. Therefore, we propose an algorithm for the extraction of outer boundaries from point clouds with uneven density for the implementation of our method.

7.6.4.1 Extraction of the Outer Boundaries of Components

Each point in the point clouds contains x, y, and z coordinate values. All points can be referenced using a defined XYZ coordinate system. The planar segments representing object components are extracted after segmentation and they are represented as plane equations in the XYZ coordinate system. However, it is difficult to extract the outer boundaries of planar segments in the XYZ coordinate system from point clouds. Thus, it is better to define the outer boundaries in a local coordinate system uvN. In the uvN coordinate system, N is the normal vector, u and v construct the plane and they are orthogonal (Figure 7-16 (A)). In this coordinate system, the points of a planar segment can be projected on the plane uv, which is the same as it is when extracting outer boundaries in a 2D space. Moreover, the uvN coordinate system is determined at the same time that the normal of the planar segment is estimated. Thus, extracting outer boundaries in the XYZ coordinate system becomes a problem of transforming planar segments into the uvN coordinate system, and then detecting the outer boundaries in the uv plane.



(A) (B) (C)



(D) (E) (F)

Figure 7-16 Steps for extracting the outer boundaries of a planar segment. (A) Calculate the coordinate system uvN; (B) Compute the ranges in the uv plane; (C) Construct scan lines parallel to u; (D) Construct scan lines parallel to v; (E) Extract the endpoints of scan lines parallel to u; (F) Extract the endpoints of scan lines parallel to v;

The proposed algorithm for extracting outer boundaries is divided into five steps. The detailed steps for extracting outer boundaries are described in Algorithm 1 and Algorithm 2.

Algorithm 1: Detecting the range of a planar segment

Inputs: point cloud of a planar segment **P**=(p1, p2, …, pn), the normal of the planar segment **Nor**
Output: the range of the planar segment in the coordinate system uvN (Range_u, Range_v)

```
(u, v)=getCoordinateSystemOnPlane(Nor);
For all points pi in P do
    p_v = pi + 3*v
    pfix_v = (p_v + pi)/2 + 2* Nor
    p_u = pi + 3*u
    pfix_u = (p_u + pi)/2 + 2* Nor

    bool isInLeft_u = false;
    bool isInRight_u = false;
    bool isInLeft_v = false;
    bool isInRight_v = false;

     For all points pj in P do
          if(j!=i)
               if ( Orientation(pj, pi, p_v, pfix_v) == “Left”)
                    isInLeft_v = true;
               if ( Orientation(pj, pi, p_v, pfix_v) == “Right”)
                    isInRight_v = true;
               if ( Orientation(pj, pi, p_u, pfix_u) == “Left”)
                    isInLeft_u = true;
               if ( Orientation(pj, pi, p_u, pfix_u) == “Right”)
                    isInRight_u = true;
          endif
     endfor

    if(!isInLeft_u)      min_u_id = i
    if(!isInRight_u)     max_u_id = i;
    if(!isInLeft_v)      max_v_id = i;
```

```
    if(!isInRight_v)    min_v_id = i;

    Range_u = distance (P[min_u_id], P[max_u_id] )
    Range_v = distance (P[min_v_id], P[max_v_id] )
endfor
```

1) Calculate the parameters of the plane equations and obtain the system uvN (Figure 7-16(A));
2) Calculate the ranges in the direction of u and v (Figure 7-16 (B));
3) Create scan lines that are parallel to the direction u and move them in the direction of v from the minimum value to the maximum value (from u_0 to u_n as shown in Figure 7-16 (C)). Similarly, the scan lines parallel to the direction v move in the direction of u as well (Figure 7-16 (D));
4) Project points on the scan lines when the distance from points to the line is smaller than the interval of scan lines. Then, extract the endpoints of all the scan line segments in the u and v directions. These endpoints are the outer boundaries of the planar segments. Consequently, the points of outer boundaries extracted from the scan lines parallel to the direction u are shown in Figure 7-16 (E). Similarly, the points of the outer boundaries extracted from the scan line of v direction are presented in Figure 7-16 (F).
5) Combine the points of the outer boundaries.

Algorithm 2 Identify the outer boundaries of planar segments

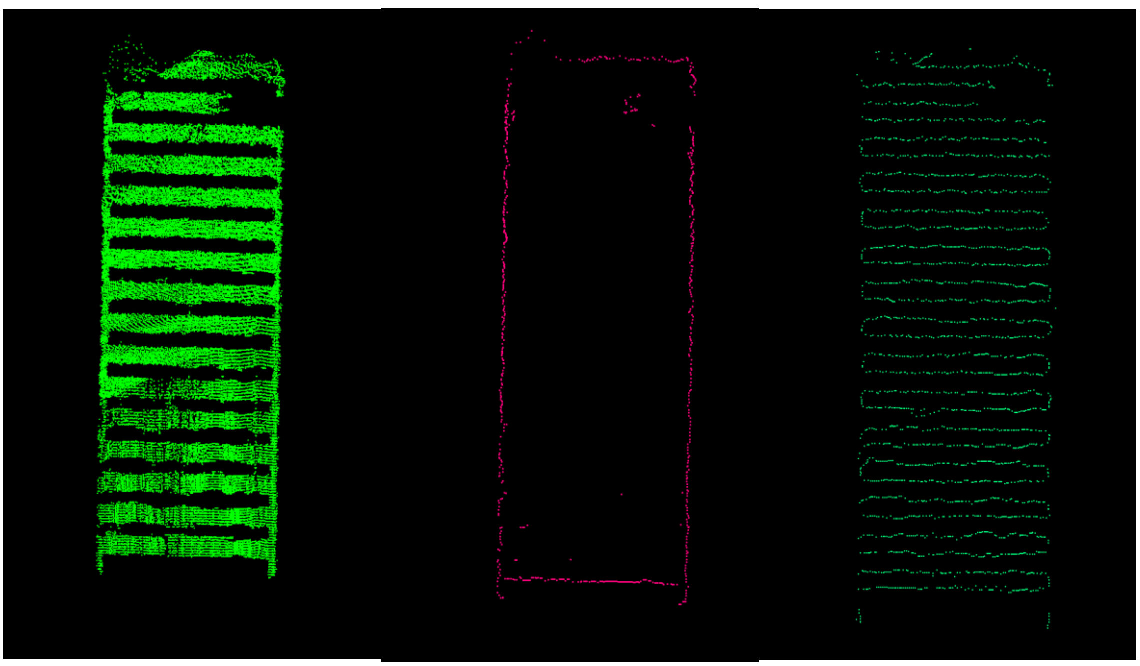
Inputs: point cloud of a planar segment **P**=(p1, p2, …, pn), the normal of the planar segment **Nor**, the interval d_inte, min_u_id, max_u_id, max_v_id, min_v_id
Output: classified outer boundaries B_{out}

```
(u, v)=getCoordinateSystemOnPlane(Nor);
int numLines_u = Range_u / d_inte
int numLines_v = Range_v / d_inte
lines_u = constructLines(u, v, numLines_u, max_v_id, min_v_id)
lines_v = constructLines(u, v, numLines_v, max_u_id, min_u_id)

For line_j in lines_u do
    For all points pi in P do
        if ( d(pi, line_j) < averageDistance(pi, KNN(pi, k) ))
            L_u ← pi
L_u_projected = project(L_u, line_j)
endPoints_u = DetectEndPoint(L_u_projected)
B_out ← endPoints_u

For line_j in lines_v do
    For all points pi in P do
        if ( d(pi, line_j) < averageDistance(pi, KNN(pi, k) ))
            L_v ← pi
L_v_projected = project(L_v, line_j)
endPoints_v = DetectEndPoint(L_v_projected)
B_out ← endPoints_v
```

We tested this method on building components extracted from point clouds. The input point cloud of a planar segment is shown in Figure 7-17 (A). Once the outer boundaries are detected, the points representing the outer boundaries are extracted, as shown in Figure 7-17 (B). To obtain the inner boundaries, we first detect all the boundary points using the algorithm for identifying boundary points based on the angle criterion in (Rusu, 2011). Then, the points of the outer boundaries presented in Figure 7-17 (B) are excluded from the detected boundaries. Finally, the points representing inner boundaries are identified, as shown in Figure 7-17 (C). In addition, the points of outer boundaries of the building components in Figure 7-11 are extracted using our proposed algorithm as presented in Figure 7-18.



(A) (B) (C)

Figure 7-17 Detection of outer boundaries and inner boundaries. (A) Input point cloud of a planar segment; (B) Points of outer boundaries; (C) Points of inner boundaries

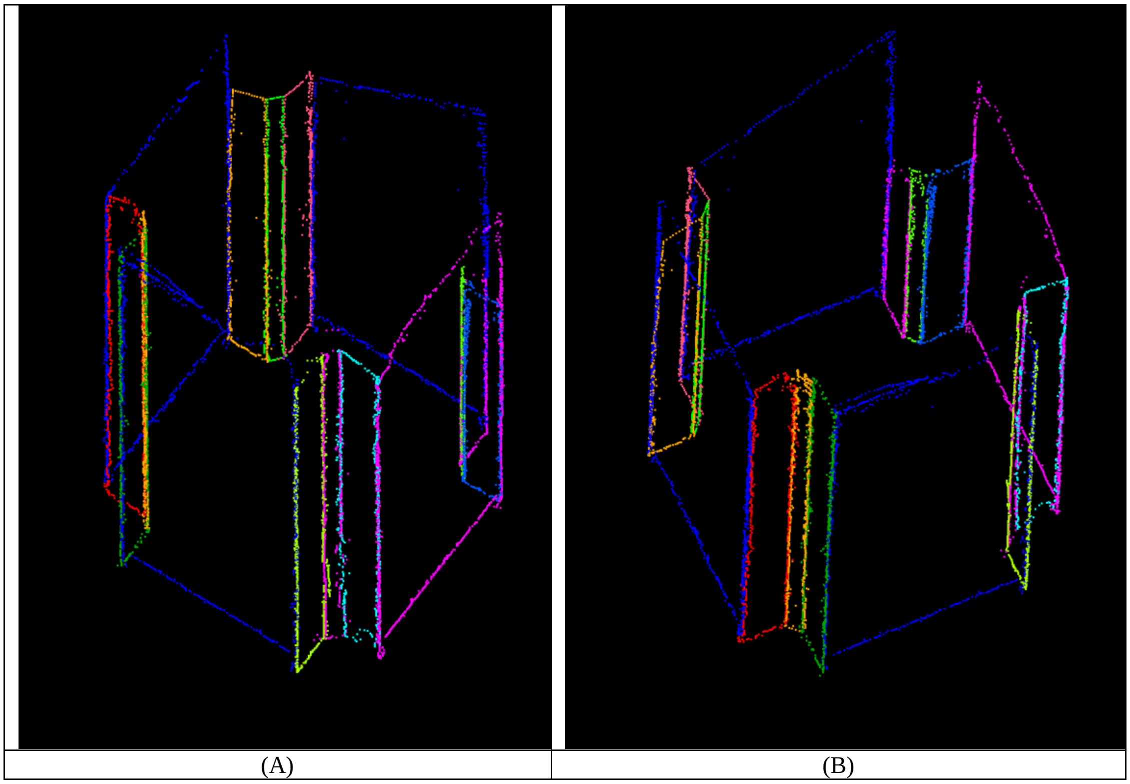


Figure 7-18 Outer boundaries of building components. (A) View 1; (B) View 2

7.6.4.2 Extraction of the Line Segments Representing Outer Boundaries

The polygon representing outer boundaries of building components are composed of line segments extracted from points of outer boundaries. For more precise representation of the boundaries of a building components, interpolated intersection lines with dense points between components are added to the planar segments before the outer boundaries are detected. If the boundary points near the intersection lines are projected on the line equations, these points are more likely to represent the real boundaries of building components.

Detecting line segments from the points of outer boundaries is an essential step in our proposed solution. For this purpose, we use RANSAC with the line model to detect the lines from the points of the outer boundaries of the components. For instance, for a component of the building shown in Figure 7-19 (A), several lines are detected (Figure 7-19 (B)). Then, the expected line segments are determined after detecting their endpoints from the points on the lines (Figure 7-19 (C)). However, in practical cases, the boundaries of components are not smooth due to outer boundaries detected from planar segments with non-uniform point density. The unsmooth boundaries of components could generate noisy line segments, which leads to difficulties in detecting line segments representing precise outer boundaries of planar segments. To decrease the noise from the points of outer boundaries and improve the quality of the detection of line segments, we propose four steps:

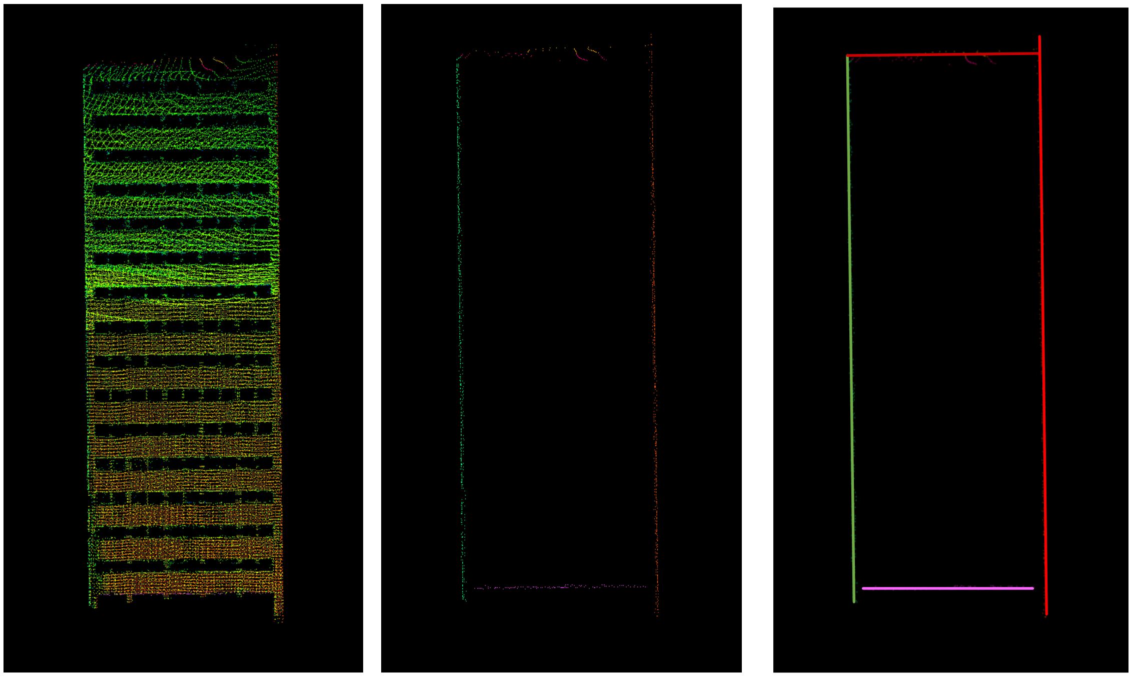


Figure 7-19 Detection of line segments representing outer boundaries of planar segments. (A) Input planar segment; (B) Detected line segments; (C) Expected outer boundaries

(1) Interpolation of line segments. This step will produce dense points on the intersection lines. The dense points on the intersection lines are helpful in extracting the line segments. As shown in Figure 7-20 (A) and Figure 7-21 (A), the interpolated intersection lines are added into the components.

(2) Smooth the points on the boundaries. The missing parts and non-uniform point density could cause unsmoothed boundaries (e.g., the components in Figure 7-17 and Figure 7-18). The noisy points could generate small line segments that are incorrect. We choose the method in (Ni, 2016) to smooth the boundary points. This method mainly involves the steps required for neighborhood refinement and the definition of a growing criterion.

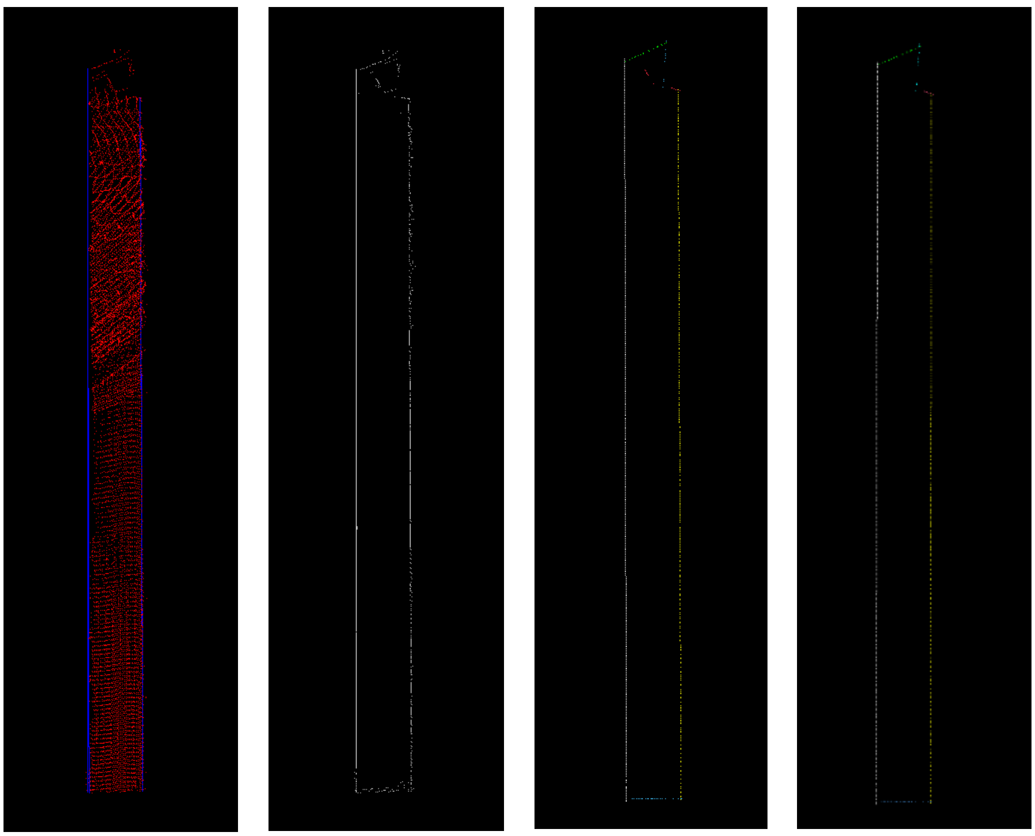
   a. In neighborhood refinement, the RANSAC algorithm with the line model is used to distinguish the inliers. The detected line containing the query point is considered as the refined neighbor, and the direction of the detected line is viewed as the principal direction of the query point.

   b. In the definition of a growing criterion, a smoothness threshold is defined to select the points that have a similar direction to the current query point. Given the point density factor, we define a distance threshold using the average point distance (e.g., 3 times the average point distance) in order to select the growing points. As shown in Figure 7-21 (B), the smoothed boundaries of all the components of the entire building are extracted.

(3) Detect line segments and filter those that do not have a large number of points. First, the line segments are detected from the smoothed boundary points using the RANSAC algorithm. Then, the small line segments with a small number of points are filtered. The line segments located in the inner component boundaries are excluded (Figure 7-20 and Figure 7-21).

(4) Smooth line segments. The points near to the line segments are projected to the line segments using line equation extracted by the RANSAC algorithm. The smoothed line segments representing the outer boundary of a component are shown in Figure 7-20 (D). The smoothed line segments of all the component boundaries of the entire building are presented in Figure 7-21 (D).

(5)



(A) (B) (C) (D)

Figure 7-20 Detection and refinement of the outer boundary of a planar segment. (A) Input planar segment with interpolated intersection lines; (B) Detected points representing outer boundaries; (C) Detected line segments; (D) Final refined line segments of the outer boundary

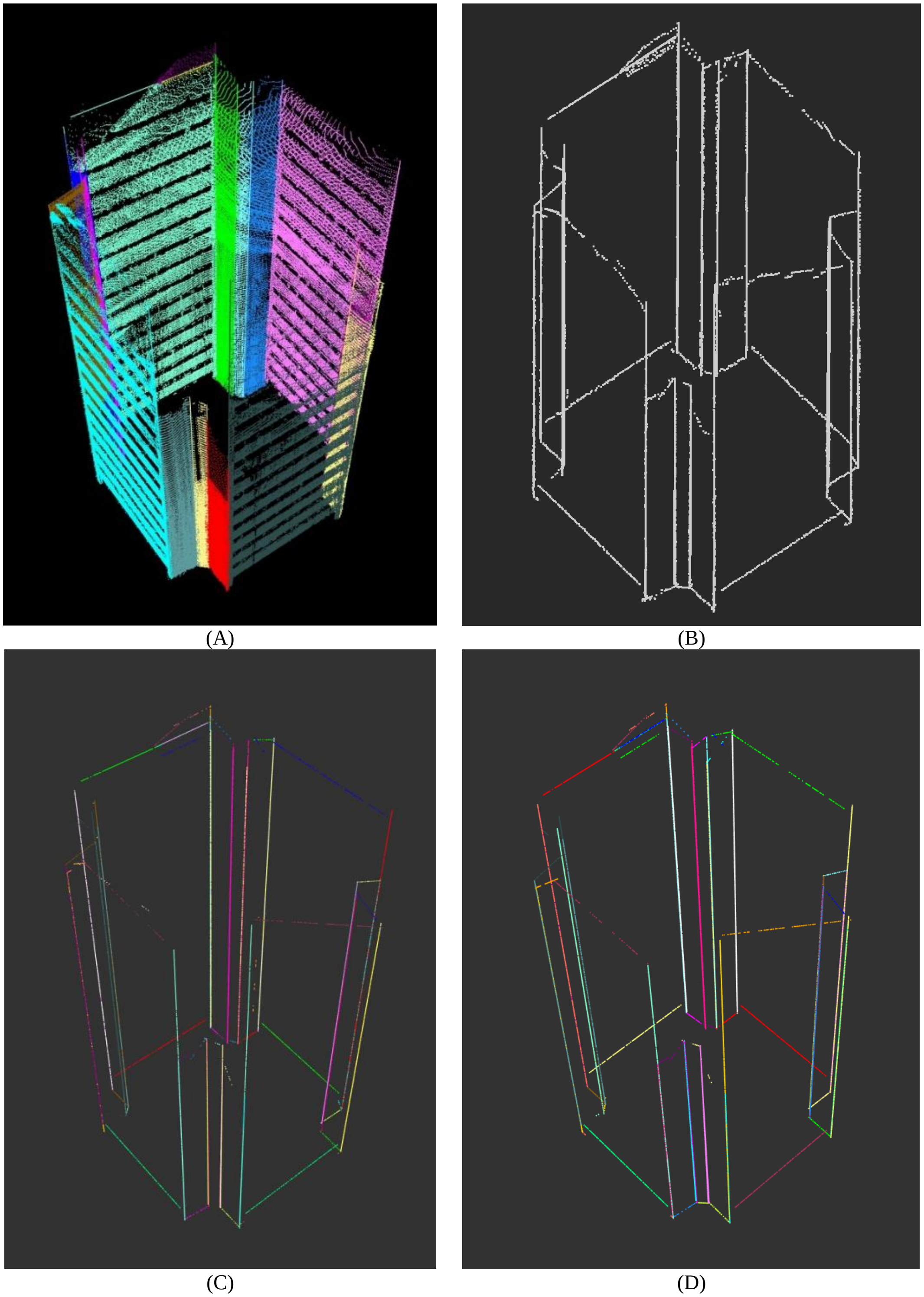
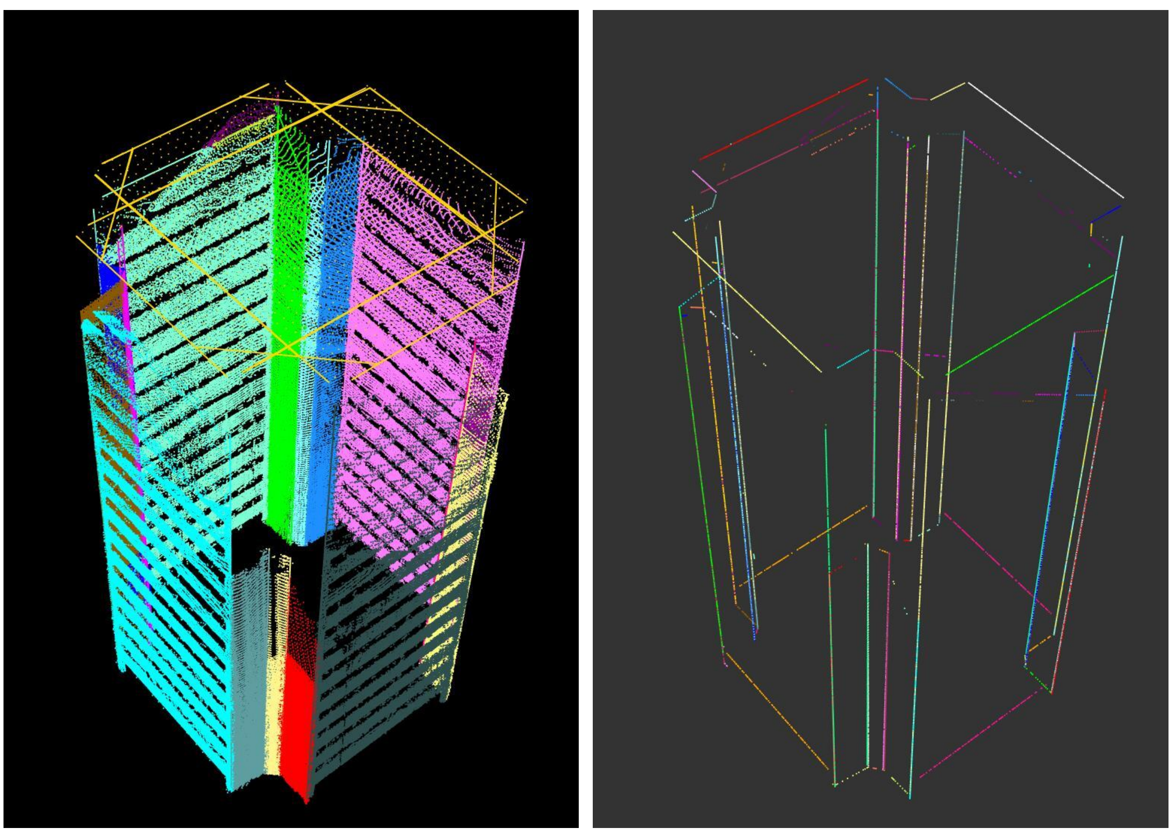


Figure 7-21 Detection and refinement of outer boundaries of a building components. (A) Input planar segments with intersection lines; (B) Extracted points of outer boundaries; (C) Detected line segments from smoothed outer boundaries; (D) Final refined outer boundaries of building components.

After executing the above steps, the line segments representing the outer boundaries of building components are detected. The inner boundary points have also been extracted. Based on the detected outer boundaries, our proposed method for completing geometric 3D models can be used to create complete geometric 3D building models from incomplete point clouds.

7.6.4.3 Completion of a 3D Geometric Model

A complete LOD2 3D building model mainly consists of roof structures and walls. Based on the work carried out in the previous steps, the refined outer boundaries of the building components are detected. When the point cloud of a roof structure observed by airborne LiDAR scanner is merged into the mobile LiDAR point cloud, all the building structures required in the LOD2 model are contained in the merged point cloud. As shown in Figure 7-22 (A), the segmentation results of the roof and walls are integrated and the interpolated intersection lines (yellow lines) between the roof and the walls are added (Figure 7-22(A)) after calculating the intersection lines. Then, the detected outer boundaries of the planar segments provide the boundary information of building components (Figure 7-22(B)), which is crucial for determining the topological relations between components. The line segments representing the outer boundaries of building components are shown using different colors.



(A) (B)

Figure 7-22 Detection of outer boundaries of the integrated point cloud. (A) Input segmentation of building components with intersection lines; (B) Refined outer boundaries of all building components

The proposed method for completing the missing parts of the building components requires the identification of the line segments representing the outer boundaries of components. Based on the steps of our proposed method (see previous sections), the sum of the cost of line segments representing the outer boundary of each component is calculated, and the components are sorted by their cost. The roof structure contains 16 line segments, and the roof has the largest cost value. Similarly, the cost of all the walls is computed. After sorting all components by cost, the component with the minimum cost value is chosen to complete its missing part. Then, using the steps described in the proposed method, all the components are processed until all the building components are in a stable state. During these steps, intersection lines are crucial for changing the order of line segments representing the outer boundaries of components to decrease the cost of the components. In Figure 7-23 (A), the intersection lines between the roof and walls all have the order value 1. Thus, the intersection lines are added to each wall as the new boundaries of the walls. The outer boundaries of the walls detected from the original planar segments are updated after adding a new line segment into the walls. The outer boundaries of all completed building components are presented in Figure 7-23 (B). The line segments represented in the same color form the boundary of a component. To create B-Rep building models, the line segments representing outer boundaries of building components require further processing, such as extending the line segments, calculating the intersecting points of line segments to make sure the boundaries of building components are represented as closed polygons and to view the completed models.

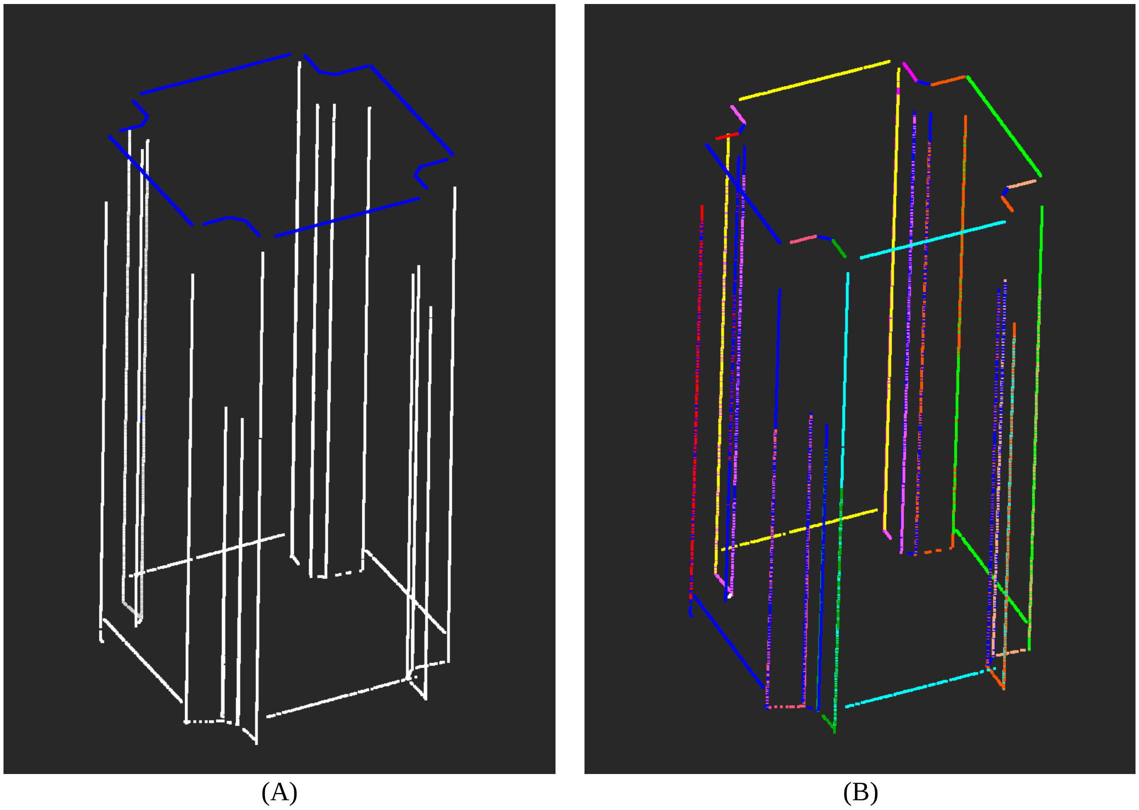


Figure 7-23 Completion of a LOD2 3D building model. (A) Outer boundaries of building components after completion; (B) The outer boundary of each component (Note: Due to the missing parts in the neighboring components, the line segments of the boundary on the intersection line cannot directly connect to the roof. After processing, the top of the wall is assumed to connect the roof. Thus, the boundary of the walls require further processing to connect the line segments and to create a closed polygon representing a wall.)

7.7 Discussion and Conclusion

In this chapter, we proposed solutions for completing LOD2 3D building models from point clouds containing occluded incomplete building components. The knowledge about buildings is integrated into the process for completing 3D geometric models. Additionally, the proposed cost function makes it possible to evaluate the incompleteness of a building component and determine where the incomplete part is. Furthermore, the cost function is crucial for creating complete models based on calculations of the cost of line segments representing boundaries and the intersection lines of building components. When the intersection lines among components and their neighbors are considered as the main constraints for creating a complete geometric model, the geometric information of components, topological relations between components and the semantic meaning of components are fundamental in determining the boundaries. The proposed solution is flexible to deal with the various types of occlusions in point clouds. However, the limitation of this solution is that it still requires further study on the creation of LOD3 building models from point clouds with occlusions because some components in LOD3 could be missing entirely and it is difficult to reason their spatial relations, topological relations and geometric information from incomplete point clouds.

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Conclusions and Future Works

1 Contributions

My doctoral research studies focus on knowledge-based automatic 3D modeling of urban areas from point clouds. In the following, I summarize the work has been done and discuss the original contributions of this thesis aiming at improving automatic 3D modeling of urban scenes for diverse applications.

First, I presented the general context and the motivation of my research work on automatic 3D modeling from point clouds of urban areas and defined the general and specific problems and the objective of the thesis. There has been a specific focus on the automatic 3D modeling of urban scenes that may be incomplete because of occlusions in a point cloud. This is a complex research issue because the missing parts of object components in urban scenes lead to the difficulties of creating complete 3D geometric models of buildings. For achieving this goal, we needed to address several specific problems: the semantic segmentation of point clouds of an urban scene, the CAD-like segmentation of object components, the extraction of the semantics of objects, the identification of topologies among object components and the completion of 3D geometric models from incomplete point clouds. For this purpose, we had proposed to benefit from the advantages of using the semantics of objects and qualitative information. In the following, the background and state of the art related to automatic 3D modeling from point clouds are presented. The fundamental algorithm of segmentation, the topologies in 2D and 3D, and knowledge representation are introduced. Finally, the existing algorithms for semantic segmentation and the solutions for completing 3D geometric models are presented and their limitations were discussed.

The main contribution of this research work is that the integration of knowledge of objects in urban scenes into the steps of 3D modeling is helpful to create complete 3D geometric models from incomplete point clouds. The main contributions of this thesis presented through chapters 2-7 are as follows.

I) Improvement of Automatic Segmentation of Complex Objects from Point Clouds

Segmentation of a point cloud allows the extraction of semantic information on objects including information on geometric shapes of objects and their components as well as their geometric relations. It allows segmenting objects components according to similar properties of points. The process of segmentation is not a trivial task and depending on the approaches used for this purpose. It may result in over-segmentation and under-segmentation of objects. In Chapter 2, we proposed new features such as the sliced directional height difference and the Difference of Normal to the existing machine learning methods to improve semantic segmentation of point clouds in addition to features derived based on the normal estimation. In Chapter 3, due to the difficulty of defining an appropriate threshold for segmenting a surface, we proposed a solution of CAD-like segmentation for decreasing over-segmentation and under-segmentation of objects. For this purpose, smooth and unsmooth surfaces are first classified. Then the thresholds for different surface types are defined in the process of CAD-like segmentation. This solution is robust to the selection of parameters for segmentation. The experiments with a LiDAR data set from a building shows that the proposed solution to address over-segmentation and under-segmentation problems more efficiently based on precision, recall, and F1-Score evaluation method. The work has done contributes to better segmenting object components from point clouds of complex urban scenes that are fundamental to create 3D geometric models and provides facts for reasoning new knowledge about objects in the proposed solution of knowledge-based automatic 3D modeling.

II) Topological Relations of Complex Object Components

Topological relations of complex object components are needed to assemble components as a whole object with a semantic label, and they are fundamental for spatial analysis in GIS applications. Moreover, topological relations between object components are crucial facts for reasoning object class and for repairing the missing parts of components based on the knowledge of urban scenes. We propose an extended RCC model for representing topological relations of complex object components. First, we discussed 4IM, 9IM, and DE-9IM in a 2D space as well as models such as RCC-3D and VRCC-3D+ for 3D objects. This allowed us to identify the limitations of these methods to represent formalized topological relations between object components in a 3D space. Considering the complexity of topological relations between two components of an object in a 3D space, we extend these methods for expressing topological relations between two planar regions that are abstracted to represent object components (e. g. a wall and a ceiling of a building). We proposed to divide these relations into four parts. The first part is the spatial relation of planes where planar regions locate. The second and third parts are the topological relations between two planar regions and the intersection line constructed by two planes where planar regions locate. The fourth part comprises the topological relations between the common parts composed of planar regions and the intersection line. These relations consist of point-point, point-line, and line-line relations on the intersection line, defined as in a 2D space. Based on the proposed model for topological relations among object components, more detailed topological relations can be formalized and represented. In the experiment carried out with test data, we present the results of extracting topological relations among building components which were mainly planar segments. This work is fundamental to formalize and represent the knowledge of objects in the knowledge base.

III) Building a Knowledge Base for Automatic Feature Recognition from Point Clouds

Semantic information plays a vital role in our proposed knowledge-based solution for improving automatic 3D modeling from point clouds in urban scenes. Semantic information allows not only recognizing and labeling objects and their components but also it helps in creating new knowledge to complete missing parts of a 3D model by semantic reasoning on both the information extracted from point clouds as well as the qualitative information stored in a knowledge base. Thus, building a knowledge base for describing and representing the knowledge of objects in an urban scene contributes to automatic feature recognition from point clouds. Using an ontology is an effective way of representing knowledge in a formalized way. Then, the knowledge is represented as rules based on concepts, properties and relations in the ontology as well as the information extracted from the point cloud (e.g., topological relations). When building a knowledge base, the concepts are organized in different modules for describing objects from different perspectives. For an urban scene, the concepts are classified according to the height criteria of objects that they represent. Hence, we have concepts describing ground objects, near-ground objects, and overground objects. Other concepts are added as subclasses of three concepts. Similarly, the "functionalities" and "natural of objects" modules are built according to the functionalities and the source of objects, such as natural or man-made objects. In addition, the geometry module is designed to represent the possible concepts of geometric shapes of objects. The "composition" module is created to describe the aggregation relations of objects in the object level and the subsystem level. Other modules such as "spatial relation", "object attribute" and "constraint" are defined as well. The "relationship" module defines the possible relations between concepts. For validating the proposed knowledge base, four experiments were proposed. The first experiment was designed to obtain complex geometric shapes composed of planar segments. The roof shape style is defined and inferred in the second experiment. In the experiments for the recognition of building components from incomplete point clouds, the capabilities of reasoning the roof shape and building features are validated based on defined semantic rules. After the validation, the experiments demonstrated that the proposed knowledge base could serve to recognize different objects from point clouds. This work showed that the knowledge of objects is important to infer new semantic information of objects from point clouds, such as roof shape style, building components, from segmentation results of objects in the steps of semantic segmentation and CAD-like segmentation.

IV) Uncertain Reasoning of Building Features from Uncertain Segmentation Results

Uncertainties existing in point clouds lead to the difficulties of extracting semantic information of objects in urban scenes. Incomplete object components segmented from point clouds could make geometric information, geometric relations and topological relations between components uncertain. This kind of uncertain information makes the reasoning process more complex and hence affects the object recognition process from point clouds. Therefore, we propose a rule-based method for uncertain reasoning of building features (such as walls, roofs, and windows) from incomplete point clouds. First, the knowledge base for formalizing and representing the knowledge of objects is required, including concepts, properties, and relations. Second, the object segmentation results are translated as the individuals of concepts in the knowledge base. For example, a planar segment is translated into the concept of "PlanarPolygon_3D" and its geometric shape. The geometric dimensions are translated into the properties of this individual. The geometric relations and topological relations between individuals are formalized as relations in the knowledge base as well. Then, for evaluating the uncertainty of individuals' information, the method of similarity evaluation between properties and relations is designed. Based on this method, the similarities between the properties and relations defined in the semantic rules and those of individuals translated from segmentation results are used to choose an appropriate semantic rule for reasoning building features. In the last step, the properties, relations, and constraints defined in the selected semantic rule are considered as important evidence to infer new semantic information. After the comparison of the properties and relations in the rule and those of individuals, the uncertainties of properties and relations are evaluated. Finally, the semantic information of this individual is reasoned with the belief in the D-S evidence theory. This work makes a contribution to infer semantic information from extracted uncertain information viewed as facts from point clouds based on formalized knowledge of objects.

2 Discussion

In this thesis, we present a knowledge-based solution for improving automatic 3D modeling of point clouds in urban scenes especially when it contains incomplete data. In our framework, we propose to integrate qualitative knowledge into the process of automatic 3D modeling. Thus, knowledge representation is required for semantic reasoning based on a knowledge base. We build a knowledge base for formalizing and describing the knowledge of objects in urban scenes. For conducting automatic 3D modeling, there are several crucial steps, including automatic segmentation of the point cloud, automatic identification of topological relations among object components, automatic feature recognition (recognize semantic information of objects and components) and the creation of complex 3D models.

In the segmentation step, pointwise semantic segmentation and CAD-like segmentation are integrated together for segmenting object components using geometric properties extracted from point clouds. For overcoming over-segmentation and under-segmentation cases, we propose to define the parameters of segmentation algorithms according to classified surface types (smooth and unsmooth) using the SVM classifier. In the final step, the solution of overcoming over-segmentation and under-segmentation is designed based on geometric reasoning. The advantage of our proposed solution for automatic segmentation is that the semantic information of points is attached and the segmentation algorithms and their parameters can be selected automatically. However, if the semantic segmentation cannot provide the correct semantic information, the segmentation algorithm and parameters could not be used to segment appropriate classes of objects.

The topological relations between object components are proposed, and topological relations between components extracted from point clouds can be identified automatically. Moreover, the identified topological relations are formalized as semantic descriptions. The topological relations between two planar regions that are abstracted as object components are determined by combining the topological relations between two planar regions and the intersection line and the relations of common parts composed of planar regions and the intersection line. This proposed model is capable of representing all possible topological relations between two planar regions in a 3D space, which is fundamental to topology querying and spatial reasoning. The proposed model for topological relations between planar regions can represent the topological relations among object components extracted from point clouds. For identifying the topological relations between extracted planar segments, the local point density is considered to determine the topological relations. Although the distance depending on point density is robust to identify the topological relations between planar segments with uneven density, the detected boundaries of planar segments and the distance threshold all could affect the results of the identification of topological relations.

Automatic feature recognition is the core part of the proposed framework for improving automatic 3D modeling of point clouds in urban areas. With uneven density and occlusions in point clouds, the knowledge of objects defined in the knowledge base helps to reason about object components and their relations. Feature recognition is conducted based on the knowledge of objects and the segmentation results of objects from point clouds and other derived information, such as geometric dimensions, geometric shape, geometric relations, and topological relations. We propose to represent knowledge about objects obtained from point clouds in a formalized way in a knowledge base, which is fundamental for automatic feature recognition from point clouds. As mentioned, the information extracted from point clouds is inherently uncertain and incomplete. Hence, it is important to consider the uncertainty in the knowledge obtained from point clouds in the feature recognition process. To address this problem, we proposed a rule-based uncertain reasoning method to deal with feature recognition from uncertain information. For this purpose, the object components segmented from point clouds are transformed into the individuals (instances) of concepts in the knowledge base. The related information of individuals is translated into properties and relations in the knowledge base. Then we develop the methods for evaluating the uncertainties of the individuals using similarities between properties and relations with respect to the prior knowledge stored in the knowledge base. After the comparison between the properties and relations of individuals and those defined in the rules, the uncertainties of properties and relations are evaluated. Then, the appropriate rule for reasoning the given individual is selected based on the uncertainties. The properties and relations in the selected rule are considered as evidence to reason its semantic information using the Dempster–Shafer evidence theory. Finally, the results of feature recognition of individuals are evaluated by the belief after combining evidence. The proposed solution of uncertain reasoning for feature recognition from point clouds can integrate the predefined semantic rules into the framework of uncertain reasoning. This solution makes it possible to take advantage of the knowledge of objects, define the necessary rules, allowing reasoning with uncertain information extracted from point clouds for feature recognition. Another advantage of this solution is that the results of uncertain reasoning are evaluated by the belief that indicates the support level of this result. However, the limitations of this solution are that we must make sure that the defined rules can precisely represent the knowledge of objects, and the information for uncertainty evaluation should first be translated into comparable properties and relations in the knowledge base.

In the step of creating complete 3D geometric models, the knowledge about building components is used to improve the completeness of a 3D geometric model based on incomplete components. We develop a solution for completing 3D building models according to the knowledge of architecture. First, the degree of completeness of building components is evaluated by the order of edges which constitutes the boundary of components. Then we consider the process of completing geometric models as an energy optimization problem. Therefore, the completion of geometric models can be implemented by a heuristic method. In this step, the knowledge about object components plays a crucial role in completing geometric models because semantic information of components combining geometric and topological information extracted from point clouds directly decides the possible connection inquired from the knowledge base. Based on this knowledge, the intersected line segments between components, boundaries of components, and completeness of components are critical information to repair the missing parts of components. In addition, we test this solution for completing LOD 2 building models with the knowledge of roof and wall. Overall, this solution is closely dependent on the quality of the results of the segmentation, and feature recognition.

As a final note, using knowledge about objects is the core of our proposed framework for improving automatic 3D modeling of urban scenes. The quality of knowledge is a very important factor in the reasoning process and the inference of know knowledge. Hence the improvement of segmentation results and feature recognition from point cloud contribute significantly to the quality of the knowledge and hence to the improvement of the 3D geometric models at the end.

3 Conclusions

The primary objective of this thesis is “to propose a knowledge-based framework for improving automatic 3D modeling from point clouds of urban scenes”. The studies from chapter 2 to chapter 7 are conducted to fulfill this overall objective. To achieve this objective, several specific objectives were addressed throughout these chapters and the hypothesis of the thesis was validated. Thus, the following conclusions can be drawn:

- Integration of automatic semantic segmentation and CAD-like segmentation allowed improving the quality of segmentation results. In addition, the proposed method allows automatic selection of segmentation algorithms and parameters to deal with the segmentation of complex urban scenes. However, there is still room for improvement in the accuracy of semantic segmentation results based on the proposed automatic approach.
- The proposed extended method for the extraction and expression of the topological relations for complex object components allows in a more effective way to extract and formally represent the topological relations between object components extracted from point clouds for man-made objects.
- Prior Knowledge is crucial for feature recognition. This is valid both for complex objects and their components. This is done with integration and comparison with more specific knowledge drown on objects and their components from point clouds. This part of knowledge

is obtained based on the segmentation results that include information such as geometric dimensions, geometric relations, as well as topological relations. The formalization of the information related to objects is the basis of the knowledge-based solution for feature recognition.

- Uncertain reasoning for automatic feature recognition from point clouds with uneven density and occlusions allows the recognition of objects and their components from uncertain information obtained from point clouds (e.g. uncertain geometric information and geometric relations, and uncertain topological relations).
- The semantic information of objects and the knowledge about urban scenes predefined in the knowledge base can be used to create complete 3D geometric models from incomplete point clouds. However, the quality of results is dependent on the quality of knowledge as well. The level of the completion of the 3D model is depended on the input knowledge and the way that the reasoning process is conducted.
- Improvements in the steps of segmentation and feature recognition steps will contribute to improving the completeness of 3D geometric models.

4 Future Works and Perspectives

The approaches presented in this thesis allowed us to go one step forward in improving automatic 3D modeling from uncertain point clouds of urban scenes. However, there are still several challenges that remain to be addressed for further improvement of automatic 3D modeling from point clouds. Future studies related to automatic 3D modeling of urban scenes include the following aspects:

- Although the advantage of machine learning algorithms has been proved in the problems of object segmentation and detection, they need a huge number of training examples to train models. In semantic segmentation of point clouds, the quality of point clouds and enough training sets make it challenging to obtain high precision of semantic segmentation results in complex urban scenes. Until now, deep learning has been explored in semantic segmentation and object detection in the field of autonomous driving. The exploration of semantic segmentation and object detection for automatic 3D modeling with different Levels of Details (LODs) is promising to improve the automation degree of 3D modeling of complex urban scenes and to extend the application range of 3D modeling in other fields.
- Developing segmentation algorithms for various types of objects is still challenging in automatic segmentation of complex urban scenes. Segmentation based on geometric

properties of object components is crucial to CAD-like segmentation. In fact, we still need to make efforts on designing adaptive segmentation algorithms for identifying geometric properties of components from point clouds with uneven density, noise, and occlusions. Although there are some clustering algorithms that provide good performance in some cases, they still require to be experimented and improved for dealing with complex urban scenes.

- Feature recognition is a complex task of automatic extraction of semantic information from point clouds of complex urban scenes. Integrating knowledge into feature recognition is a feasible solution for automatic feature recognition. Thus, knowledge acquisition and knowledge representation are prerequisites to using knowledge in feature recognition. Efforts for decreasing the difficulties of knowledge acquisition and knowledge representation are required to ensure knowledge can be easily integrated into many fields. In addition, reasoning with semantic information is one of the deficiencies of machine learning. The research on knowledge reasoning could solve the problems of uncertain reasoning in feature recognition.
- Point clouds include rich spatial information on objects. The progress in automatic information extraction from point clouds in computer vision could improve the automation of 3D modeling of urban scenes. Additionally, the combination of images and point clouds makes it possible to improve semantic segmentation, object detection, and scene understanding because images are the complement of point clouds in the aspects of spatial resolution, color.

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