Building Structural Characterization using Mobile Terrestrial Point Cloud for Flood Risk Anticipation

Mémoire

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Résumé

Compte tenu de la fréquence élevée et de l'impact majeur des inondations, les décideurs, les acteurs des municipalités et le ministère de la sécurité publique ont un besoin urgent de disposer d'outils permettant de prédire ou d'évaluer l'importance des inondations et leur impact sur la population. D'après les statistiques, le premier étage des bâtiments, ainsi que les ouvertures inférieures, sont plus susceptibles de subir des dommages lors d'une inondation. Ainsi, dans le cadre de l'évaluation de l'impact des inondations, il serait nécessaire d'identifier l'emplacement de l'ouverture la plus basse des bâtiments et surtout sa hauteur par rapport au sol. Le système de balayage laser mobile (MLS) monté sur un véhicule s'est avéré être l'une des sources les plus fiables pour caractériser les bâtiments. Il peut produire des millions de points géoréférencés en 3D avec un niveau de détail suffisant, grâce à son point de vue depuis la rue et sa proximité. De plus, l'augmentation du nombre de jeux de données, issues des MLS acquis dans les villes et les environnements ruraux, permet de développer des approches pour caractériser les maisons résidentielles à l'échelle provinciale.

Plusieurs défis sont associés à l'extraction d'informations descriptives des façades de bâtiments à l'aide de données MLS. Ainsi, les occlusions devant une façade rendent impossible l'obtention de points 3D sur ces parties de la façade. Aussi, comme les fenêtres sont principalement constituées de verre, qui ne réfléchit pas les signaux laser, les points disponibles pour celles-ci sont généralement limités. De plus, les approches de détection exploitent la répétitivité et les positions symétriques des ouvertures sur la façade. Mais ces caractéristiques sont absentes pour des maisons rurales et résidentielles. Finalement, la variabilité de la densité de points dans les données MLS rend difficile le processus de détection lorsqu'on travaille à l'échelle d'une ville.

Par conséquent, l'objectif principal de cette recherche est de concevoir et de développer une approche globale d'extraction efficace des ouvertures présentes sur une façade. La solution proposée se compose de trois phases: l'extraction des façades, la détection des ouvertures et l'identification des occlusions. La première phase utilise une approche de segmentation adaptative par croissance de régions pour extraire la boîte englobante 3D de la façade. La deuxième phase combine la détection de trous avec une technique de maillage pour extraire les boîtes englobantes 2D des ouvertures. La dernière phase, qui vise à discriminer les occlusions des ouvertures, est en cours d'achèvement. Des évaluations qualitatives et quantitatives ont été réalisées à l'aide d'un jeu de données réelles, fourni par Jakarto Cartographie 3D Inc., de la province de Québec, au Canada. Les statistiques ont révélé que l'approche proposée pouvait obtenir de bons taux de performance malgré la complexité du jeu de données, représentatif des données acquises en situation réelle. Les défis concernant l'auto-occlusion de certaines façades et la présence de grandes occlusions environnantes seront à étudier plus en profondeur afin d'obtenir des informations plus précises sur les ouvertures des façades.

Abstract

Given the high frequency and major impact of floods, decision-makers, stakeholders in municipalities and public security ministry are in the urgent need to have tools allowing to predict or assess the significance of flood events and their impact on the population. Based on statistics, the first floor of the buildings, as well as the lower openings, are more likely subject to potential damage during a flood event. Thus, in the context of flood impact assessment, it would be required identifying the location of the buildings' lowest opening and especially its height above the ground. The capacity to characterize building with a relevant level of detail depends on the data sources used for the modeling. Different sources of data have been employed to characterize buildings' facade and openings. Mobile Laser Scanning (MLS) system mounted on a vehicle has proved to be one of the most reliable sources in this domain. It can produce millions of 3D georeferenced points with sufficient level of detail of the building facades and its openings, due to its street-view and close-range distance. Moreover, the increase of MLS providers and acquisitions in towns and rural environments, makes it possible to develop approaches to characterize residential houses at a provincial scale.

Although being effective, several challenges are associated with extracting descriptive information of building facades using MLS data. The presence of occlusion in front of a facade makes it impossible to obtain the 3D points of the covered parts of the facade. Given the fact that windows mostly consist of glass and laser signals could not be reflected from the glass, limited points are usually available for windows. While the repetitive pattern and symmetrical positions of the openings on the facade makes it easier for the detection system to extract them, this characteristic is missing on the facade on rural and residential houses. The inconsistency of the point density in MLS data make the detection process even harder when working at city scale.

Accordingly, the main objective of this research is to design and develop a comprehensive approach that effectively extracts facade openings. In order to meet the research project objective, the proposed solution consists of three phases including facade extraction, opening detection, and occlusion recognition. The first phase employs an adaptive region growing segmentation approach to extract the 3D bounding box of the facade. The second phase combines a hole-based assumption with an XZ gridding technique to extract 2D bounding boxes of the openings. The last phase which recognizes holes related to the occlusion from the openings is currently being completed. Qualitative and quantitative evaluations were performed using a real-word dataset provided by Jakarto Cartographie 3D inc. of the Quebec Province, Canada. Statistics revealed that the proposed approach could obtain good performance rates despite the complexity of the dataset, representative of the data acquired in real situations. Challenges regarding facade's self-occlusion and the presence of large surrounding occlusions should be further investigated for obtaining more accurate opening information on the facade.

Contents

List of Figures

List of Tables

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Preface

This thesis contains an article that has been published in a peer-reviewed journal. Chapter 2 of the thesis is devoted to this article.

The chapter contain the original content of the article: Haghighatgou N., Daniel S., Badard T., "A method for automatic identification of openings in buildings facades based on mobile LiDAR point clouds for assessing impacts of floodings", *International Journal of Applied Earth Observation and Geoinformation*, *108*, p.102757. Date of publication: 29 March 2022. Compared to the submitted version, slight changes have been made on the numbering of sections/figures/tables/ in order to retain the consistency with the rest of the thesis.

Author Status and Contribution Niloufar Haghighatgou, the author of this thesis, is the first author of the inserted article. Her contribution includes investigating current state of the research field, conceptualizing, and developing the methodology, conducting the experiment, validating, writing, and revising the manuscript, all under supervision of thesis director and co-director.

Introduction

Context

The need for flood risk anticipation, as an emergency response to one of the ruinous types of natural disasters, is increasing by the continuous ascending of the temperature of the Earth's climate system, known as global warming. For some regions, such as southern Quebec, Canada, this need is heightened because of the harsh winters with frequent precipitation, as well as relatively short summers. Accordingly, the freezing of the waters followed by ice-jams melting have caused annual and even seasonal flooding in such regions (Oubennaceur et al., 2019; Ouellet et al., 2012).

“On April 17th, 2019, an ice-jam gave way, sending icy water on to roads, even into the buildings' basement, in Beauceville”, reported by a Canadian public broadcaster. This damage affected around 300 buildings including 230 residential buildings in Beauceville, Quebec, Canada. There have been notable flood events that occurred across Canada, from Alberta to New Brunswick like Saguenay flooding in 1996, Red River flooding in 1997, and Alberta flooding in 2013, to mention a few. This natural disaster is of great importance since it has the potential to cause significant losses. Not only it can put the lives of thousands of people into danger, but it also has direct damage to the economy up to billion, i.e., costs of compensation for personal belongings, furniture, and building reconstructions (Oubennaceur et al., 2019). Besides, coastal and riverside residences in such regions might be always under the stress of being exposed to a flood event.

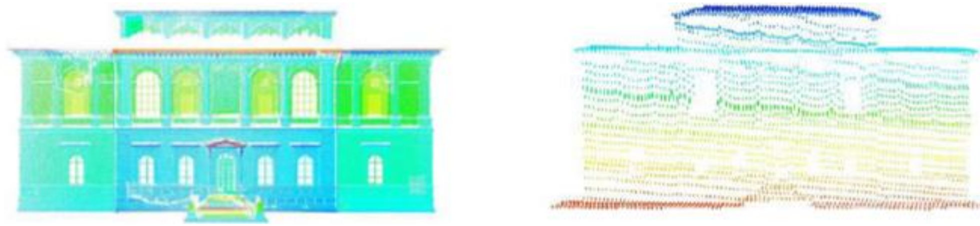
Following by the increase of flooding events in the province of Quebec, a research project, entitled ORACLE-2, has been started since 2019, by the public security ministry of the province, in order to assess the impact of flooding events on the population, at the province scale (Badard et al., 2021). This project, which mainly focuses on the flood-prone areas, aims at providing comprehensive knowledge of the buildings, including occupational and structural, in order to better help the decision process regarding the risks associated in the flooding context. Based on statistics, the first floor of the buildings, as well as the lower openings, are more likely subject to potential damage during a flood event. Thus, in the context of flood impact assessment, it would be required identifying the location of the building lower openings and their height above the ground. Having such information, the height level of a flood that could go through a building could be inferred as well as the damage and costs, if it does go through.

Aiming for quantifying the expected damages, flood risk assessment has been addressed in various research studies. Oubennaceur et al. (2019) proposed a probabilistic approach to predict the expected flood damage in a residential area nearby the Richelieu River, southern Quebec. This study considered four building categories based on the one-story/two-stories buildings and the presence/absence of a basement. However, this approach only considered an average measurement of the first-floor elevation for each of the building categories. A study on the city of Dresden (Germany) was carried out to develop a flood loss model to characterize the vulnerability of buildings based on 3D city models and variables representing building geometric properties (i.e., building area, height, roof type, and density of buildings) (Schröter et al., 2018). Validation of the predicted model confirmed that the employed set of variables plays an important role in improving the performance and reliability of the model. However, details on building openings were not used in this study due to the unavailability of such data in 3D city models. 3D city models, such as CityGML, provide 3D representations of buildings with accurate 3D geometric information in different levels of details (LoDs) which are widely developed for various environmental simulations (Stoter et al., 2016). While lower LoDs (i.e., building footprint, building height, and roof shape) are included in 3D city models, the higher level of detail (i.e., building openings) is mostly unavailable (Schröter et al., 2018).

Although a great deal of attention has been devoted to 3D modeling of buildings, the level of detail in these models remains relatively low. In addition, previous studies were conducted based on the characteristics of building in cities which usually include facades with regular structures. However, flood-prone areas, such as rural environments, with a variety of facade structures having various opening types, even on one facade, have been receiving less attention in the context of building characterization. Therefore, research efforts are required to characterize buildings of various structures, and in particular facades, at a level of detail sufficient for the assessment of the impact of flooding on them

Problem statement

The capacity to model building with a relevant level of detail depends on the data sources used for the modeling. Different sources of data have been employed to reconstruct the buildings' facade and openings including aerial-based data, UAV-based data, and ground-based data. Although all these data sources are relevant in terms of level of detail, they have different characteristics regarding resolution, precision, and accessibility. Figure 0.1 illustrates an example of different point density in LiDAR point cloud data when collected either from the ground or from an airborne platform. Several research studies were conducted on the detection of facade windows using oblique airborne LiDAR and optical datasets (Tuttas and Stilla, 2013, 2012; Zhang et al., 2015). The experimental results demonstrated that this type of data source is mostly capable of reconstructing the building or solely the facade, but not the detailed objects (Burochin et al., 2014; Xiao et al., 2012). UAV-based datasets, on the other hand, indicate to be applicable for facades objects retrieval. Yet, the unavailability of this type of data sources, make UAV-base type of data less convenient.



a. Terrestrial LiDAR data (~200points/m2) b. Oblique view LiDAR data (~5-10 points/m2)

FIGURE 0.1 – Comparison of different point density in LiDAR data (Tuttas and Stilla, 2012)

Amongst the different data sources on facade objects reconstruction, ground-based sources of data, either LiDAR point clouds or optical images, confirmed to fulfill the most promising results. Not only they provide the building's facade, but also, they contain additional information for a higher level of facade detail retrieval (e.g., height of the first floor and basement opening). Given the time allotted for the completion of this master's project, the focus has been only on LiDAR point clouds acquired with Mobile Mapping Systems (MLS) for which optical images are recorded, but not necessarily co-registered (no colorized point cloud available). As a result, in the following, only this type of ground-based data source will be explained and considered.

Terrestrial mobile LiDAR point clouds have significant characteristics that make them advantageous for the sake of building facade characterization. For example, an MLS can produce large-scale spatial information (i.e., georeferenced X, Y, Z coordinates as well as the reflected laser beam intensity) in a given time budget that reduce the processing effort for obtaining the third dimension. However, the processing of the resulting point cloud faces several challenges when aiming for the detection of openings, namely windows and doors. The main issues that will be discussed further include: (1) limited reflectivity of the opening; (2) presence of occlusions; (3) lack of repetitive pattern; and (4) point density changes.

(1) Limited reflectivity of the opening: The LiDAR laser beam is not reflected by the glass and pass through instead. As a result, the laser beam is reflected by objects behind the openings, unless there are curtains. Therefore, the presence of openings in a house facade frequently results in the presence of holes in the point cloud. The size and shape of these holes will depend on the presence of curtains or objects near the opening as well as the shape of the window crossbars.

(2) Presence of occlusions: The presence of objects in front of the house facade generates occlusions in the LiDAR point cloud. Most of the street-level occlusions occur in front of the first floor, such as trunk, vegetations, and car, which result in low information regarding the lowest building openings (Xia and Wang, 2019). Such occlusions also take the form of holes (i.e., absence of points) in the point cloud at the facade, leading to ambiguity with openings. Additionally, self-occlusions of the facade frequently occur due to the oblique viewing angle of MLS system.

(3) Lack of repetitive pattern: Unlike building facades of urban areas, openings on the facades of residential houses in rural environments do not follow a repetitive pattern and symmetrical positions on the facade. While these regular alignments and similarity of opening types makes it easier for the detection system to extract the openings, it is not possible to consider this assumption when working in rural or flood-prone contexts.

(4) Point density changes: When working with MLS data at a city-scale, point density is changing significantly according to the distance between the LiDAR and the surveyed object and the sensor viewing angle (Gollob et al., 2020). This inconsistency in the point density induces different representations of the same object and makes its identification more complex.

Research question

Taking into account the importance of retrieving the information characteristics of a building opening, especially on the first floor in the context of flood risk assessment, and the related issues using mobile LiDAR point cloud data, as mentioned earlier, the following research question arises:

- How to extract the location and height above the ground of buildings' first floor and assess the altitude of the bottom point of the buildings lower opening by means of LiDAR point cloud considering the main issues in this context including the limited reflectivity of the openings in addition to the presence of occlusions, the varying point density, and the diversity of the openings' styles with non-repetitive patterns in rural and flood-prone environments?

Research hypothesis

Generally, before going through the detection task using LiDAR data, a segmentation approach is usually applied in order to extract the building facade. Based on the literature, several segmentation approaches exist in an urban context. Model fitting approaches, such as RANSAC, are able to detect different forms of primitives from the points, like planes. However, they are highly sensitive to point density and noise. In addition, some approaches further enhance the segmentation by adding optimization methods to the processing. While being robust to noise, this type of approach leads to expensive computation costs. Region growing approaches have also been employed considering their easy implementation. However, the performance of the approach highly depends on the two major factors of seed point selection and growth criteria which needs to be accurately selected.

After performing the segmentation, the opening detection task is applied. To do this, holes on the facade are usually detected as the facade openings. Based on the processing environment, some approaches extract the holes in the 3D space either by applying Triangulated Irregular Networks (TIN) on the points, which is capable of detecting openings of different shapes and sizes, or employing an operator dedicated to finding the holes of rectangular openings. Other approaches project the point to a 2D space (i.e., rasterization), having less complexity compared to the 3D representation of the points, to find the holes related to the openings inside the resulting 2D raster of the facade. It should be noted that successful detection of the opening holes in the resulted raster highly depends on the quality of the detected facade. Moreover, assumptions of regularity and similarity of the openings on the facade are frequently used in the approaches found in the literature. However, these assumptions limit the detection to urban area contexts where building facades usually have similar structures and contain openings with regular size and positions.

Statement of the research hypothesis

Building's lowest opening and the altitude of the first floor of residential houses in city-scale datasets consisting of mobile LiDAR point clouds can be characterized by extracting the building facade using an adapted region growing segmentation and detecting the openings using rasterization-based hole detection.

Research objectives

General objective

The main objective of this research is to design and implement a comprehensive approach that effectively extracts facade openings involving an adapted region growing segmentation and a rasterization-based hole detection method.

Specific objectives

1. Design and develop a segmentation approach, dedicated to facade extraction, using a region growing method adaptive to variation of point density in mobile LiDAR dataset.

2. Design and develop a facade opening extraction approach, using a rasterization-based method adaptive to mobile LiDAR dataset containing residential houses with different shape, size, and context.

3. Design an approach to detect holes related to occlusions considering window shape regularity and occurrence of points in front of the hole.

Methodology

Three major phases are considered for the main body of the solution to meet the specific objectives of this research, which are illustrated in Figure 0.2. The first phase aims at extracting a 3D bounding box containing all the points related to the building's facades. In the context of the ORACLE-2 project, the full point cloud recorded by the MLS is not processed at once. Each house is processed individually. To do this, the point cloud associated with it is extracted by taking advantage of its footprint. Thus, the preselected point cloud of the house is segmented using region growing segmentation to partition the building into its main components. Then, segments related to the main walls are identified and further merged to obtain a connected facade segment.

The second phase performs the extraction of facade openings with the aim of finding the height of the first floor, as well as the bottom part of the lowest opening(s) as the final output. Since the openings mainly consists of glass parts for which no points are available (i.e., glass is transparent for the LiDAR beam), this phase uses a rasterization method to extract the holes inside the facade segment as the openings. This method is applicable to openings with different shape and size.

Since occlusions close to the facade also result in holes inside the facade segment, the last phase aims at recognizing openings versus occlusions. To do this, two assumptions are considered to mark holes as openings or occlusions. The first assumption is the shape regularity of the detected holes since in general, an opening would result in a hole with a regular shape inside the facade wall. The second assumption is the occurrence of points in front of the detected holes corresponding to objects located in between the house and the LiDAR systems.

The relevance and performance of the proposed approach have been assessed through dedicated experiments. A first series of tests was conducted at the end of the first phase to evaluate the ability of the segmentation approach to extract facades. It was not a question here of extracting the facades as well as possible but of detecting and circumscribing them sufficiently to detect openings there. A second round of testing was conducted at the end of the second phase. The aim here was to quantitatively evaluate the detection of openings in terms of the number correctly identified, their correct location and their completeness.

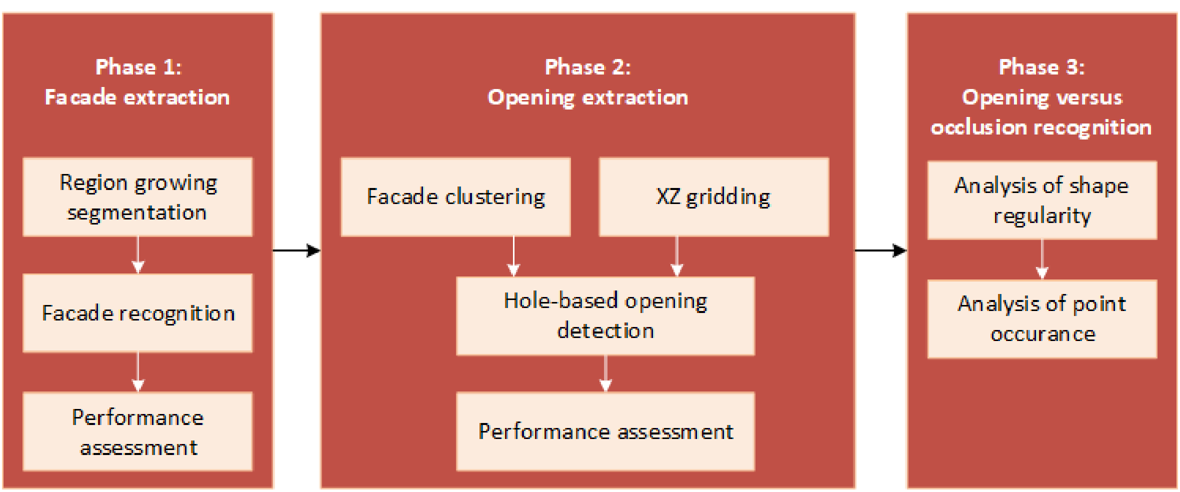


FIGURE 0.2 – Methodology diagram

Structure of the thesis

The introduction section has briefly explained this research project by presenting the context, problem statement, hypothesis, objectives, and the methodology employed for this research. In the following, chapter 1 provides a comprehensive review of the current research that explored building segmentation and opening detection using ground-based sources of data including LiDAR point cloud and optical images. Chapter 2 includes brief explanation of the proposed approach, the used data set with a short description, as well as results and discussion for each phase. This chapter is proposed as a paper that has been published in the International Journal of Applied Earth Observation and Geoinformation. The conclusion chapter presents a synthesis of our main contributions and direction for future improvements.

Chapter 1 Literature review

This section presents opening detection approaches using either ground-based optical image or LiDAR datasets, their contributions, as well as lack of generalization in some cases. Although this research project focuses on the detection of openings using mobile LiDAR point cloud, a comprehensive investigation of methods using various datasets and not only mobile LiDAR point cloud has been done. Accordingly, several common approaches using optical images are also included in this section in order to present a better overview of the available approaches and their potential and challenges in this context.

1.1 Image-based approaches

The extended availability of close-range urban images like Google-street-view database, and of a wide range of image processing techniques have attracted the attention of many researchers towards high quality urban reconstruction tasks. There exist two general categories of approaches exploiting street-level optical images, which are 2D-based, and 3D-based approaches. The following subsections present proposed methods of each category.

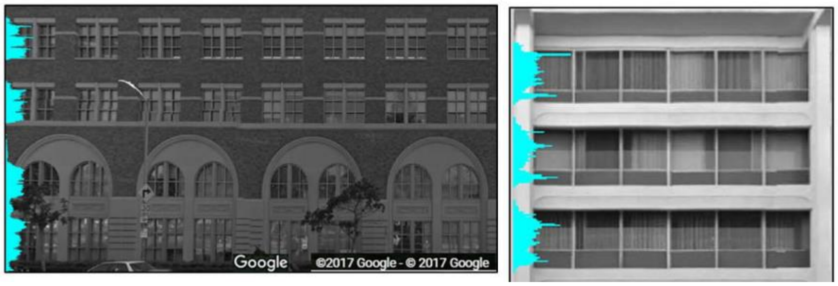
1.1.1 Approaches using series of 2D images

Wide variety of approaches employed street-level images for investigating building facade objects that include realistic texture information. Burochin et al. (2009) employed a single rectified street-level image to extract rectangular regions of the facade using an unsupervised hierarchical segmentation. The proposed method first separates available facades in an image from each other and the surrounding objects, and then, segments the facade by splitting the facade region. However, this research did not provide the semantic information of the facade objects and needs to be extended for a detailed interpretation of the facade. Kostelijk (2012) proposed a method to extract building 3D model and employed the gradient information of a rectified image for the window detection task. It is applicable to a facade image with rectangular-shaped windows. The method first looks for the corners of the windows. A window corner is defined as the intersection of a vertical-horizontal pair (V-H) of window borderlines. Thus, the method is made up of 6 main steps namely: extracting curves, distinguishing straight lines using Hough transform, detecting V-H candidates, selecting V-H related to windows, extracting window corners, and finally constructing the windows. When no corner could be extracted while V-H lines candidates were available, the candidate V-H lines were extended or trimmed. As the method works with gradient information, different lighting situations could affect the result.

Neuhausen et al. did notable research on automatic window detection of the facade images exploiting a cascade classifier technique. First, in a comprehensive review (Neuhausen and Koch, 2016), they categorize window detection approaches into three main categories: a) grammar-based, b) pattern recognition, and c) supervised machine learning approaches. Regarding grammar-based approaches, the review concluded that a simple shape grammar with a few rules could tackle the problem of time-consuming procedure for a high quantity of facade images. These approaches would lead to rectangle facade splitting including window and non-window elements. Going from simple to more complex grammar rules, the system gets more biased to specific facade types so that it may be no longer generally applicable for different architectural styles. Pattern recognition strategies usually rely on a couple of assumptions including regularity and symmetry of the facade. This idea is valid for office towers and modern buildings that exhibit repeated structure. While for small houses, this type of approach could be more challenging. Machine learning approaches, on the contrary, do not rely on such assumptions and could make use of inherent image characteristics that could be widely applicable even when going from one architectural style to another which would be true in a large-scale dataset. However, one should be careful with the type and quantity of employed features since they directly affect the results. In addition, gathering a proper set of labeled training data sets needs considerable effort. Following this detailed review, Neuhausen et al. developed a machine learning system for window detection using a multiscale classifier satisfying the needs of risk assessment analysis (Neuhausen et al., 2018, 2017; Neuhausen and König, 2019, 2018). The system applies a sliding window detector of multiple sizes over the entire image to detect facade windows using a boosted cascaded classifier. The proposed method is inspired from the object detection framework of (Viola and Jones, 2001) and soft cascaded classifier proposed by (Bourdev and Brandt, 2005) that were originally developed for face detection. This method employs automatic weighted combination of several weak classifiers at each stage deduced by Haar-like features that removes the necessity of prior manual selection of a classifier and enables detecting windows of different shape and size with higher detection rate. With the emergence of deep neural networks, alternative solutions have been proposed in the machine learning category. Thus, Schmitz and Mayer (2016) trained a fully convolutional network for pixel-wise segmentation of a facade by means of augmented patches of the image. Augmented images, which are generated by scaling, rotating, adding noise, or etc., were used to have a larger amount of data for training. As for Liu et al. (2017), they were the first to segment a facade using a deep convolutional neural network on a full image scale based on symmetric characteristics of man-made structures.

Shape grammar approaches have been frequently proposed for semantic facade image segmentation. Teboul et al. (2010) method learns facade shape dictionary using supervised random forest classification by means of a new set of 30 rectified images of annotated building facades namely Paris2010. The results are iteratively optimized based on the probability estimations obtained by the randomized forest. Results on several facade images indicated that the proposed method performs better than when classifying the images using random forest independently, especially for the windows that are covered by vegetation, represent other objects of the scene due to reflection and transparency, or when a part of the facade, including windows, is exposed by strong shadow. Contrariwise, instead of assigning a label pixel by pixel, the proposed method takes advantage of regularities of the facade grammar to reconstruct the missing windows. Teboul et al. (2011) further introduced a semantic grammar-based segmentation using Reinforcement Learning to control the complexity of the shape parsing problem which resulted in a considerable speed-up compared to previous methods. Riemenschneider et al. (2012) generated an irregular lattice for parsing a 2D facade structure that is not limited to fixed grammar rules and is able to handle more complex structures, thanks to the Graz50 data set they created which consists of 50 images of various locations including classical, historical, and modern building styles. Both Paris2010 (Teboul et al., 2010) and Graz50 consist of semantic classes such as windows, wall, balcony, door, roof, shop, and sky, while the latter presents a wider range of facade layouts. Mathias et al. (2016) proposed a bottom-up approach for facade parsing which combines the low-level information of semantic segmentation with higher level information of object detectors to obtain advanced labeling. Unlike (Teboul et al., 2011) method which defines a full facade grammar compatible with specific structures, an adaptable framework was introduced here in which the architectural principles could be removed or added for different architecture style. The output is defined boundaries and structures that can be used for facade modeling.

Using several images to cover the entire facade, Oskouie et al. (2017) proposed a gradient-based method as a bottom-up approach to find the facade layout information so that enough accurate knowledge for defining a split grammar as a top-down approach could be extracted. To reconstruct the entire facade area, they first used an available building footprint as the input and assigned each image to the corresponding building wall by estimating the camera's position and applying a structure from motion procedure. The gradient-based method involved some vertical and horizontal gradient histograms computation and analysis. Two general types of facade layout were considered in this work, namely connected and disconnected facade elements, as shown in Figure 1.1 Connectivity is assessed along, respectively, the vertical and the horizontal axes. Such analysis allows determining whether windows, for instance, touch each other or are isolated on the facade.



(a) Facade type 1 with disconnected elements (b) Facade type 2 with connected elements

FIGURE 1.1 – Facade layout characterization using the projection of vertical gradients presented by cyan graph (Oskouie et al., 2017).

The information of the detected elements was used to generate the facade's split grammar. While the building footprint was used as the starting point for the facade detection, the building height was estimated based on the detected rows that demonstrate the number of building floors. The proposed method tries to use general features of the facade elements and to be independent from specific facade style. However, based on the presented results, the method is likely to be more applicable for multi-level buildings with relatively high numbers of windows and doors rather than a small house. In addition, empirical and automatic thresholding is considered in various steps of the method, which makes it limited to specific facade type.

Very recently, a hierarchical method has been proposed based on topological graph to parse facade image and reconstruct a semantic facade model, assuming the building has a regular arrangement as a type of man-made objects (Wang et al., 2020). For example, the windows are arranged vertically-horizontally, a balcony is always at the bottom of a window, or a door intersects the ground level (Figure 1.2). The proposed method first generates the overall facade layout graph inspired by prior knowledge about the primary topological properties of the facade. Then it reconstructs the complete facade according to the generated graph, in which the attributes of the graph nodes are used to reconstruct the facade. The proposed method demonstrated promising results. However, the data does not include any case with a basement.

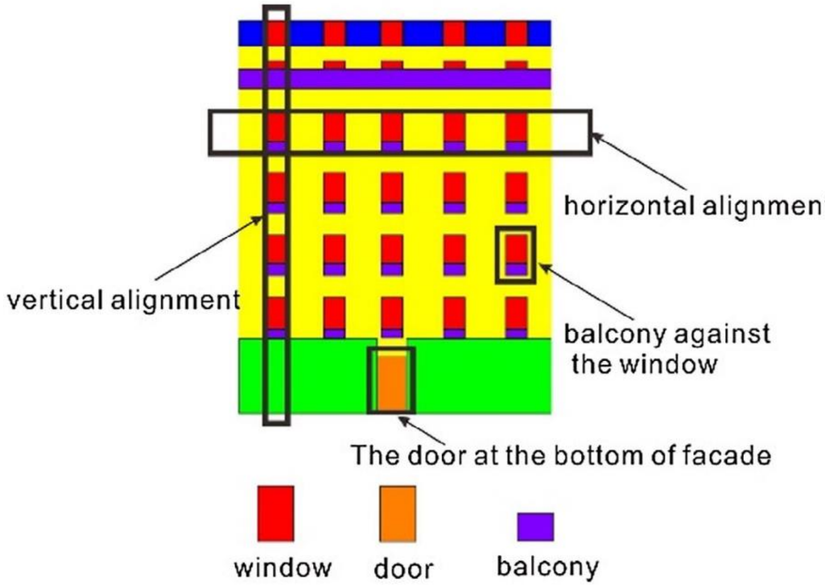


FIGURE 1.2 – Topological properties of a facade (Wang et al., 2020)

1.1.2 Approaches using image-derived 3D point clouds

Pénard et al. (2005) proposed a robust method to present a 3D model of a building facade. Using 3D point clouds derived from a set of multi overlapping calibrated images, they generated a textured mesh to reconstruct the final facade. Nguatem et al. (2014) proposed a knowledge-based automatic approach for localizing facade objects using a 3D point cloud derived from image matching. Within a probabilistic framework, the proposed method performed three main steps: a) facade segmentation, b) object localization, and c) window and door model selection. Authors stated that due to the rich diversity (i.e., size, shape, or style) of man-made objects like buildings and their elements, all approaches for reconstructing such objects needed a model selection step. For detailed applications, often several rough models fit the data and then different methods could be considered to refine the rough model. This research works resulted in good localization of windows. However, its application is limited to the provided templates.

1.1.3 Occlusions

Not so many research studies made an effort to retrieve the occluded parts in a facade image. (Bénitez et al., 2010) refer to street level objects such as cars, vegetation, and pedestrian as unpredictable occlusions. They proposed a method to detect occlusions in context where ground-based LiDAR and optical data are collected simultaneously. After selecting several rectified images of the facade from a moving vehicle system, occlusions are first detected using laser point clouds. This is done by analyzing the 3D points related to the ground and refining the detection through the projection of the detected occlusion points into facade images. Finally, using an inpainting technique (Rasmussen and Korah, 2005), occluded areas of the facade are estimated from the pixels surrounding these areas, for the cases where there is a large object near the facade and the occluded part cannot be seen in any of the camera positions. The pixels are interpolated iteratively by searching the most similar patch around each pixel. Some methods rely on the repetitive structure of the facade and estimate the occluded windows using non-occluded ones (Vračar et al., 2016). Wang et al. (2020) method proved to achieve promising result using topological graphs. Indeed, the reconstructed facade included almost all the openings, except for a few strongly occluded doors. As shown in Figure 1.3, openings occluded by trees and balconies were fully reconstructed. However, it failed to fully reconstruct the doors in the presence of cars.

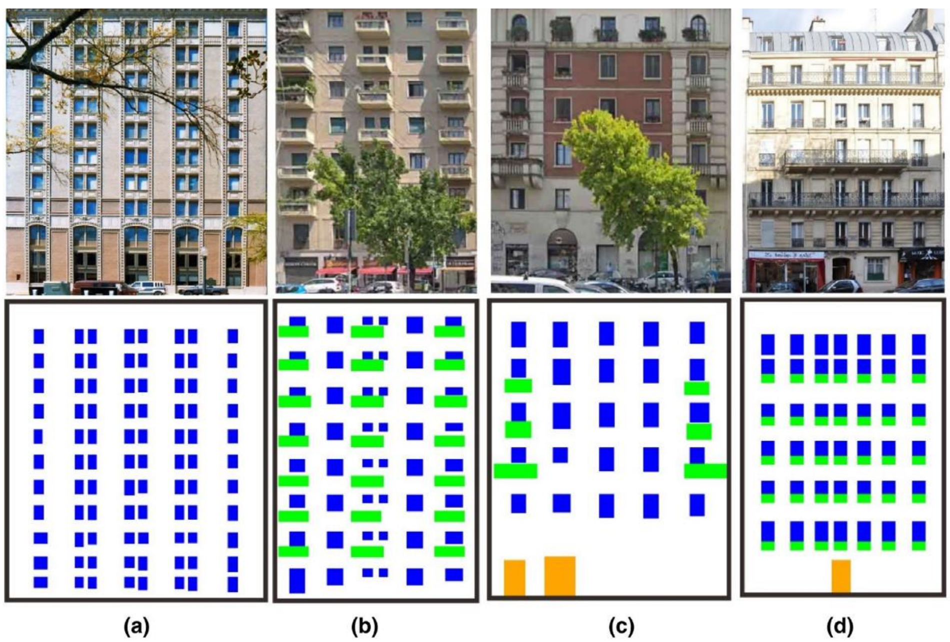


FIGURE 1.3 – Facade reconstruction in the presence of street-level occlusions (Wang et al., 2020)

1.2 LiDAR-based approaches

Using 3D point clouds to detect facade openings has been an active research field for more than a decade. Research works that specifically extracted facade windows mostly employed only ground-based point clouds, leading to lower performance than less developed method utilizing a combination of LiDAR and optical ground-based data sets that provided better results. Contributing methods and some issues regarding window extraction using LiDAR or combined LiDAR-optical datasets are introduced in the following subsections.

1.2.1 Pre-processing prior to opening detection

Prior successful segmentation of the 3D LiDAR point clouds decreases the processing time and enhances the accuracy of the latter feature extraction task, namely detection of the openings in this research. Segmentation here refers to grouping the 3D points of an urban scene into segments related to the ground, roof, and different sides of a building facade. This has been a long-lasting research topic. Accordingly, plane detection is the first step in segmentation processing. Related methods could be generally categorized into four strategies: a) clustering, b) energy optimization, c) region-growing, and d) model fitting (Grilli et al., 2017; Xu et al., 2020). Among these categories, region-growing and model fitting strategies are frequently seen in literature (Pu and Vosselman, 2006; Wang et al., 2012; Zolanvari and Laefer, 2016). Clustering strategies refer to methods that group points sharing common spatial position, geometries, or attributes into primitives by comparing points in a defined neighborhood. The efficiency of this category relies on the selection of calculation criteria and optimal threshold (Xu et al., 2020). Energy optimization strategies that formulate the plane segmentation are frequently used for refinement of the initial segmented plane set (Dong et al., 2018). While being robust to noise and clutter, these methods lead to expensive computational costs (Xu et al., 2020).

Random sample consensus (RANSAC) (Fischler and Bolles, 1981), and Hough transform (HT) (Ballard, 1981) methods are two widely used methods in model fitting category that are being performed in the spatial and parametric domain, respectively. RANSAC groups raw point clouds into segments in which a maximum number of inliers can fit the plane model (Xie et al., 2020). The method is effective if the facade does not include lots of protrusions and similar details (Zolanvari and Laefer, 2016). For improving the efficiency, Wang et al. (2012, 2011) proposed a method that first computes normal vectors of the non-ground points using principal component analysis (PCA) to generate surface patches, and then employs RANSAC to segment different facade sides by fitting a plane to the generated patches. HT method, which employs a voting strategy, finds points sharing the same plane by inspecting local maxima in the parametric domain (Vosselman et al., 2004). RANSAC method proved to be more effective than the HT method (Grilli et al., 2017). Although both methods are generally advised for plane segmentation, the efficiency relies on an acceptable quality of the point cloud, weak noise, and low outliers (Xu et al., 2020).

Region growing methods perform a repetitive process by first getting a seed unit (point, voxel, hybrid) and then inspecting if the neighboring units can join to grow the seed considering the spatial distance and similar properties (Xie et al., 2020; Xu et al., 2020). Accordingly, the performance of such methods relies on the selection of the growth criteria (similarity measure), and the selection of the seed. Unlike using this method in an image application that can search for the neighbors using pixel coordinates, there is no information in the unorganized LiDAR point cloud to inspect the neighboring points (Deschaud, 2010). Kd-tree is a common method that calculates the similarity for k nearest neighbor units of the seed (Rabbani et al., 2006). Voxel, supervoxel, and octree structures are also frequent which pre-cluster the points using a pre-defined resolution as the basic unit for the growing process (Dong et al., 2018; Xie et al., 2020). For the similarity measure, normal vectors, the distance between the growth units, or the combination of these two are being used. (Wang et al., 2011) computed normal vectors of the points based on the neighboring points placed in a $3 \times 3 \times 3$ voxel region centered at the point and if the number of points in the neighborhood was less than three, they did not consider the point. On the contrary, (Rabbani et al., 2006) considered the k nearest neighbors of the point to calculate the normal vector. By using a fixed number of neighboring points, they adapted the measurement to varying point density since a bigger region is used for points with lower density. Lastly, for the selection of the seed point, a common way is considering points whose residuals are less than a threshold. The residual of a certain point, which could be obtained by measuring distance or curvature, is calculated by considering a fitting plane on the point and its neighbors (Rabbani et al., 2006; Xie et al., 2020). Owing to their easy implementation, region growing methods are widely used for plan segmentation. However, the effectiveness of such methods depends on the growth criteria and seed unit which needs to be adjustable for the different dataset, especially due to varying point density and outliers (Xie et al., 2020; Xu et al., 2020).

Aijazi et al. (2013) proposed a segmentation method to classify an urban scene into six basic urban objects, i.e. road, building, car, pole, tree, and unclassified, which was later extended for the facade feature extraction task in (Aijazi et al., 2014). The proposed segmentation method first segmented the point cloud into voxels and then converted them to super-voxels. This conversion was applied by assigning specific properties to a voxel, namely geometrical center, voxel size, variance, and mean. The super-voxels were then grouped as objects using a proposed Link-Chain method in which each super-voxel was considered as a link of a chain, and an object was grown by attaching neighboring links. Eventually, these objects were classified considering local descriptors, and geometrical features.

Employing human knowledge of the facade has been also proved to be advantageous for segmenting point clouds of facade. Some methods use such information to segment different facade element excluding windows and further employ additional processing for window detection task (Pu and Vosselman, 2009a, 2007). However, another approach is to build a knowledge tree to simultaneously segment the facade to dominant elements including windows (Luo and Sohn, 2010).

1.2.2 Opening versus occlusion detection

The presence of occlusions in front of a building facade causes considerable confusion for machine understanding also when using a 3D LiDAR point cloud for building facade reconstruction. As will further discuss, method mostly interpret holes of the facade's point cloud as openings since glass barely reflect laser beams. However not all the holes in the facade correspond to openings, but some are related to occlusions in front of the facade. Thus, it is important to figure out which one is the cause of the holes on the facade's point cloud in order to be able to reconstruct the openings.

Similarly, as image-based approaches, some methods in this LiDAR-based category consider the repeated structure of the building and detect the representative windows to compensate for the effect of partially occluded ones (Hao et al., 2018; Wang et al., 2012, 2011). However, other approaches overcame the occlusion issues by removing or not considering some parts of the point cloud. Thus, (Wang et al., 2012, 2011) omitted the ground floor since it had a different pattern of openings (ex. presence of door) from the other floors. Sadeghi and Arefi (2019) eliminated the effects of occlusions by using a series of morphological operations on the connected components extracted from the facade binary image. A. K. Aijazi et al. (2014) reconstructed the incomplete area caused by moving occlusions (car, people) by collecting point clouds of the same facade in multiple passages on different days or at different hours of the same day. Besides, the 2D projection of the road was used to reconstruct the lowest outline of the facade since it is often occluded by moving or static occlusions.

1.2.3 Opening detection using LiDAR only

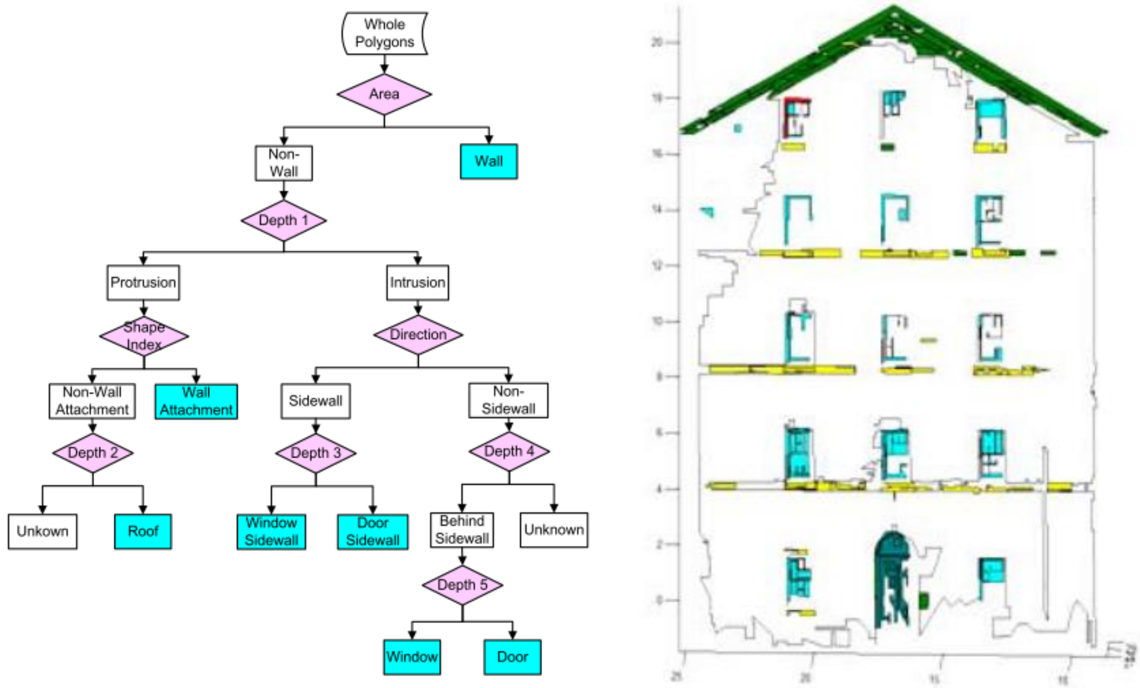
Some opening detection approaches are based on the assumption that windows hardly reflect the emitted laser pulse to the sensor since windows mainly consist of glass. Thus, holes resulting from limited laser pulses of windows are used to define their location. (Pu and Vosselman, 2009a, 2007) proposed an approach for automatic extraction of windows from 3D point clouds derived from Terrestrial Laser Scanner (TLS) data. Two categories of windows are distinguished based on the assumption that glass reflects no laser beam: windows not covered with curtains, and windows covered with curtains. Windows of both categories are assumed to leave holes in the facade wall segment, because windows without curtain barely reflect the laser beam while available points for windows with curtain are not usually in the same plane as the facade which again causes holes on the facade segment. A Triangulated Irregular Network (TIN) is generated to detect long TIN edges in a wall segment that appear at the inner boundaries (holes) of the wall. The end points of the TIN edges generate the window boundary points. Before the window detection step, the authors utilized a previously developed method (Pu and Vosselman, 2006) that extracts common facade elements (wall, roof, door, and extrusion) using additional human knowledge of facade construction attributes, namely size, orientation, and position of facade elements. Although this study brings up an assumption (window-hole) that is valid for most of the building, it requires additional knowledge on the building to primary segment the facade. This knowledge does not contain context where there is an occlusion in front of the windows, which could result in false or incomplete detection. In addition, the method works effectively as long as the architectural style of the building facade remains unchanged. As an example, the door is assumed to intersect the ground while this assumption is not true for houses with stairs on the first floor. The method is later enhanced by adding RGB information provided by optical images (Pu and Vosselman, 2009b).

Wang et al. (2012, 2011) further investigated hole-based methods to detect windows of a facade using mobile LiDAR data. After using a sequence of PCA-RANSAC algorithms to find the facade, the window detection approach starts with a voxel-based representation, simultaneous window frame points selection and window crossbar points elimination. To execute this, a rule-base operator is designed according to the window pattern to classify window points. Four different types of window borders, namely two horizontal borders at the top and bottom of the window, and two vertical ones at the left and right side of the window, are considered. A point belongs to the upper horizontal window border if upper neighbor points are found while at the same time no lower neighbor points are found. The same concepts are applied to find the other three window borders. After detecting window borders' points, window location is found through histogram analysis along with horizontal and vertical directions. To do so, the horizontal and vertical projections of the points are obtained by sweeping a plane through each direction individually to count the total number of points in each of the planes. As a result, two histograms are generated in which sharp peaks indicate the window location. Window size and spacing are automatically inferred to generate a pattern constraint to use for occluded windows, especially windows on the first floor. (Zhou et al., 2018) also employ the same steps to detect window using 3D laser point clouds. Despite the applicability of Wang et al. method, there are still some drawbacks when considering the purpose of this research. It is worth noting that before applying the window detection step, the authors simply exclude the ground-floor points (from 10 to 30 percent of the facade's lower part depending on the type of the building) from the window detection processing, since the pattern of the ground floor is different from the rest of the facade due to existence of door and special windows. In addition, the method fails to detect non-rectilinear windows or glass buildings given the limited number of points on the facade. Also, the designed operator uses constant values which are defined experimentally based on the pattern of the facade.

Similarly as the previous works, Aijazi et al. (2014) detect windows using holes in 3D point cloud recorded using a mobile mapping system. The proposed method refines the results by combining symmetrical and temporal correspondence on the facade to complete the occluded parts of the facade. The method main steps are as follows. After segmenting and classifying the 3D point cloud into urban classes (i.e. facade, road, car, pole, tree, and unclassified), the 3D points related to both building facade and road surface are projected onto a known arbitrary plane which is parallel to the facade. Then, the outmost boundary of the facade is extracted. To avoid inconsistency due to the presence of dynamic occlusions such as cars or pedestrians, 2D projection of the road surface is considered here as the lowest line of the facade boundary. Afterward, point inversion within the extracted facade boundary is applied. As a result, points only exist for all hole areas, including window-holes. Finally, symmetrical and temporal features are estimated to refine the detection through statistical analyses. Since buildings usually consist of repetitive patterns and self-similarities, symmetrical windows are determined by comparing the distances between their centers in both row and column. The temporal features rely on multiple acquisitions of the 3D point clouds through multiple passages in the urban scene, either on different days, or at different times of the same day. Doing so, corresponding windows in successive passages (temporal correspondence) are obtained to complete windows where no symmetrical correspondence is found or occlusions exist in front of the facade. Although this method presented successful results regarding the detection of windows with different shape and size, its major strength is the addition of temporal correspondence to the processing.

Zolanvari and Laefer (2016) employed a slice-based procedure in addition to window-hole assumption to extract opening's boundary points from 3D point clouds of sufficient density regardless of the data acquisition system (either image or LiDAR acquired from a terrestrial or aerial platform). The proposed method sections the building into defined vertical and horizontal slices regardless of the building complexity, and searches for the gaps along each slice to detect gaps that could be caused by windows. First, it roughly segments out the facade using RANSAC algorithm to obtain roof, wall, and other group of points sharing similar geometrical features. Then, it equally slices the facade plane horizontally and vertically to distinguish openings from the solid wall area by detecting gaps in each slice. To accelerate the processing, each slice is projected as a line along its lower local x-axis. The points are later transferred back to their original positions. A gap in the facade plane is selected if the distance between a point and its two closest neighbors is bigger than twice the median distance of points along the corresponding line, which is calculated along horizontal and vertical slices respectively. In the final steps, the points in the outermost k cm of the detected gap are selected as the opening boundary. Using this method would be advantageous since openings of different shapes could be detected in quite a faster computational time compared to other approaches. In addition, no prior knowledge of the facade is required. Window curtains and doors that are on the recessed plane would not be included in the initially RANSAC-fitted facade plane. However, if too many points were collected for the recessed curtains and doors, the facade plane may shift behind the real plane and thus user interaction would be necessary to find the best threshold for the facade plane. More importantly, even though gaps result from both windows and occlusions in front of the facade, the method does not consider the gap related to the occlusions and it assumes that if there is a gap, there should be a window, because it used a high-density merged aerial-terrestrial dataset of facade and assumed the existence of minimum occlusions in front of the facade. Another slice-based method is proposed by (Hao et al., 2018) for facade reconstruction of modern buildings. The proposed method starts by segmenting the point cloud to find the planar surfaces. Then, each facade is sectioned into vertical slices using a series of computations. The window detection task is conducted considering the assumption of similarity and regularity of the windows in an individual facade, employing a template-matching method. Window frames are classified into different categories based on their similarity and completeness. Ultimately, after finding the repetition of windows, a window template is fitted at the location of window frames intersection (horizontal and vertical frame lines). The results of the proposed method proved to be capable of reconstructing a convex-concave facade in addition to a planar facade. However, the method depends on some parameters in both slicing and window reconstruction steps. In the window retrieval task, the method would be more applicable in terms of detection since a template is fitted to a window even if the window is partially scanned and there exists only one corner of the quadrate frame. Thus, if the exact location of a window border is sought, there is a need for more reliable computation. It is also stated that before extracting windows, points inside the oriented bounding box of the facade are clustered using a distance-based clustering algorithm and then clusters near the highest and lowest elevations of the wall are removed since there is mainly no window in these areas in modern buildings. Conversely, in the context of our research project, we could state that basement windows are placed in the lowest part and mostly intersect the ground in most of the residential buildings.

Other proposed methods considered prior human knowledge of the facade. The same ontological notion, which was previously used by (Pu and Vosselman, 2007) for segmenting the facade, is used in (Luo and Sohn, 2010) to form a hierarchical classification tree for 3D facade modeling. First, point cloud segmentation and outline extraction are applied to extract segment polygons. Then, based on the most common dominant features of the facade, namely wall, window, sill, door, roof, and sidewall, a hierarchical knowledge tree is generated to encode the characterized facade knowledge. In order to classify the extracted polygons, four types of attributes are used: area, depth, shape index, and direction. Afterward, threshold selection is applied to all features' attributes. As an example, the polygon related to a window should be smaller than a possible wall (area constraint), not have a thickness greater than a threshold (depth), and so on. Detailed constraints are included in Figure 1.4a. where cyan rectangles indicate the facade elements. According to the confusion matrix that is employed here for quality analysis, windows are well detected. However, the proposed method would not result in reliable window localization. Indeed, due to the unavailability of 3D points in glassy parts, except a few, windows are mostly detected based on the available window frame points, which are also incomplete (Figure 1.4b). In addition, the method employed a supervised classification that is directly proposed based on particular facade elements and their properties, which may not be available in other cases and may need to be improved/modified based on the area of study in further projects.



(a) Hierarchical knowledge tree

(b) Final classification result with yellow segments as wall attachment, cyan segments as windows, and pine green as door

FIGURE 1.4 – The procedure and final result of the 3D facade modeling (Luo and Sohn, 2010)

Nguatem et al. (2014) also developed a knowledge-based method to localize windows and doors in 3D point cloud of facades within a probabilistic framework. Although they used point clouds derived from image matching, the method would also be applicable when using 3D LiDAR point cloud. More detail on this work has been presented in section 1.1.2. Sadeghi and Arefi (2019) proposed a method for 3D modeling of a building using a handheld laser scanner system. After grouping the 3D points into ground and non-ground, facade points are separated from street-level occlusions, which are also included in the non-ground points. Conditional RANSAC is used here to detect the facade plane while keeping window sills and niches. Then, depth image is generated using the point cloud and two histograms in the x and y directions are generated on the depth image to eliminate irrelevant object points. Finally, facade elements are extracted using another histogram perpendicular to the facade plane. As shown in Figure 1.5, by analyzing minimum and maximum peaks of the histogram, indentation, and protrusion indicating window, door, and walls are separated. Morphological operations are further applied to fill the gaps of the connected components of the detected elements. Despite considering the idea of removing points related to the occlusions using depth image, the rest of the processing lack generalization.

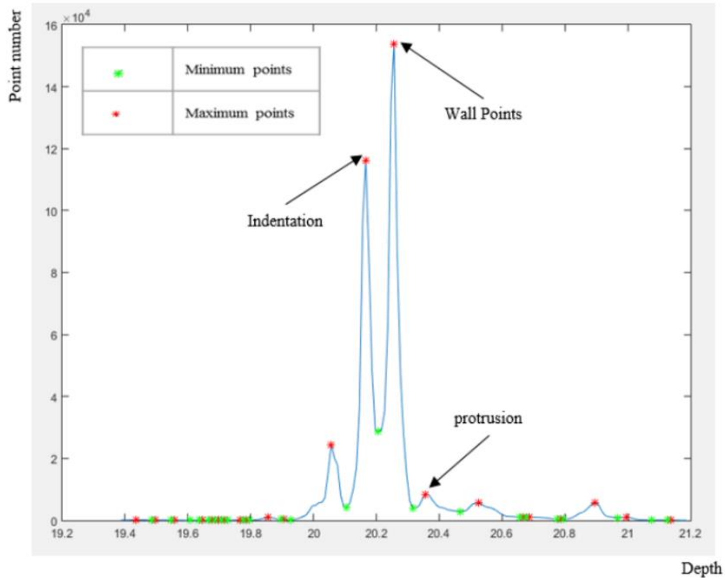
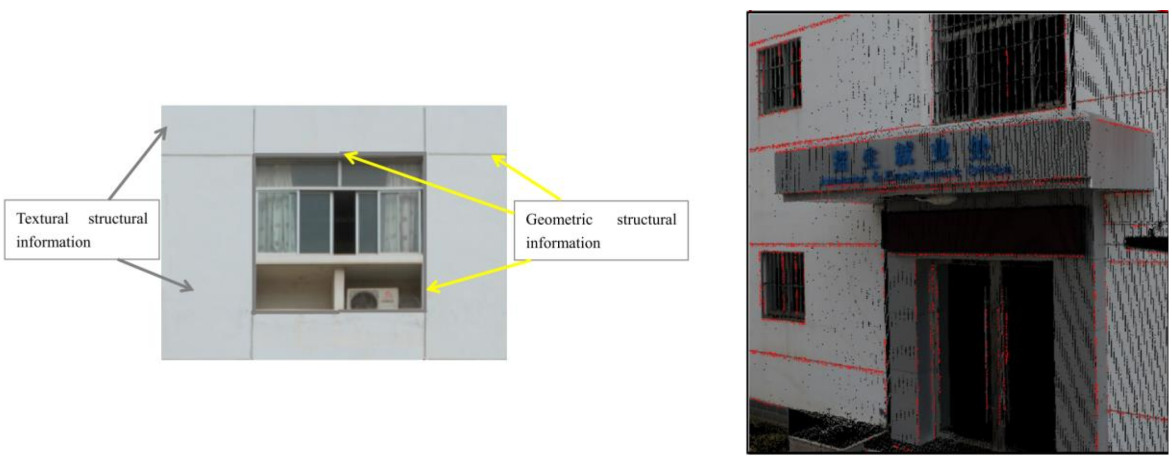


FIGURE 1.5 – Depth histogram with indentation as niches and protrusion as window and door (Sadeghi and Arefi 2019)

1.2.4 Opening detection using combined LiDAR and optical images

Facade features extraction methods are improved by adding ground-based RGB color information to previously unstructured 3D point cloud data. Ali et al. (2008) proposed a method for extracting rectangular windows utilizing morphological operation and contour analysis. They evaluated the proposed method on an RGB textured LiDAR point cloud of a mobile mapping system. LiDAR data is converted into distance images, and image processing techniques such as morphological operations and contour analysis are employed to obtain connected components. This 3D to 2D conversion results in information loss. (Pu and Vosselman, 2009b) proposed a semi-automatic method for facade reconstruction from combined information derived from terrestrial LiDAR data and close-range image. Extracting planar features from LiDAR data using (Pu and Vosselman, 2009a, 2007) method in combination with line segments from multiple-view close range images, the facade's general structures is discovered. Actually, multiple-view images are primarily used to generate occlusion-free texture of the facade. To do this, histogram analysis is employed to distinguish background laser points (facade) from foreground laser points (occlusion). Projecting foreground points to the images, occlusions are excluded from the final texture. This research work presented interesting results evaluated on small residential houses. However, presence of basement are not considered. Yang et al. (2016) proposed a method for boundary extraction by taking advantage of combined LiDAR-optical image information. Boundaries are initially extracted from the image and further refined through the co-registered point cloud. Authors presented promising results; however, curve boundaries could not be modeled using this method.

Combining the advantages of 3D point cloud data and 2D optical images, Wang et al. (2018) propose a method for accurate facade features extraction from 3D point cloud with a focus on structural information. First, using the textural and geometrical information of the 2D optical image (Figure 1.6a) facade features are extracted as line segments. In this regard, a series of computations, i.e., image pre-processing, texture manipulation, gradient calculations, and line detection, are applied. Then, pixels of the extracted line segments are mapped into the 3D point cloud considering the one-to-many relationship between 2D pixels and 3D points. Finally, using the RANSAC algorithm, facade feature extraction of the 3D point cloud is optimized considering structural information. A comparison using different feature extraction methods is done to express the effectiveness and accuracy of the proposed method, including range-image extraction and optical image method in the absence of structural information. However, this method still has some potential limitations considering the purpose of this research. The number of line features may increase when the texture of the building becomes more complex. Additionally, the presence of multiple types of geometric structures in the facade or occlusion can result in a decrease of the final accuracy. More importantly, the method does not include any window detection/localization but some features that could jointly form a window. Figure 1.6b shows the result.



(a) An example of structural information on an image of a building facade

(b) Final extracted features of the building on a small portion of the dataset where red lines indicate the extracted features overlapping with the original 3D point cloud

FIGURE 1.6 – structural information of the facade and the extracted features considering structural information (Wang et al. 2018)

1.3 Summary

This section described facade's opening detection approaches using 2D images, 3D LiDAR point clouds, and merged LiDAR-optical datasets acquired either from terrestrial or mobile acquisition system. Methods using images fall into two categories, namely methods using images (from one to series of images), and methods using image-derived point clouds. Methods of the first category have employed a wide variety of approaches such as shape grammar, pattern recognition, machine learning, and deep neural network. The second category that has attracted less attention employs analysis of the segmented planes of the facade.

Methods using LiDAR point clouds inevitably consider a pre-processing prior to the opening detection task. This step, which is mostly employed due to lack of structure, massive volume of the points, and heterogeneity of the point density, segments the 3D points based on their similar characterization. PCA and RANSAC are two famous methods in this domain. LiDAR-based methods commonly take advantage of the window-hole assumption due to the fact that windows mostly consist of glass and the glass offers limited reflectivity. Thus, they detect the holes in the facade segment to locate windows. However, not all holes in the facade segment are a sign of window but are due to the presence of occlusions in front of the facade. The detection of facade windows has been improved by using merged LiDAR-optical datasets. Extracting planar surfaces from 3D LiDAR point clouds combined with boundary information derived from 2D continuous images has made it possible to obtain results that are more accurate.

While the presence of an occlusion in front of a facade is inevitable, methods sometimes ignore this issue in their procedures. Research studies that consider such cases mostly assume the repetitive pattern of the facade to reconstruct the occluded parts. However, this assumption is effective for modern regular buildings. Two different types of occlusions could be considered: static and dynamic. The effect of dynamic occlusions such as pedestrians or cars proved to be reversed by using multiple passages on different days or the same day in different hours. In the case of static objects, such as trees or poles, using data of a facade from different viewing angles could be effective for an accurate facade element retrieval.

A great number of references have been reviewed that could partially fulfill the needs of this research. Most of these research studies demonstrated interesting results in the task of opening detection of modern or office tower buildings, which present regular repetitive structures and do not include a basement as in small residential houses. It is also noticeable that fewer methods have been devoted to detecting doors as well as the building's first floor. In general, the majority of relevant approaches, while highly effective in the domain of building reconstruction include limitations with respect to generating detailed spatial and geometrical information related to openings. Dominant limitations are a) applicability to only rectilinear window styles, b) prior facade knowledge requirement, c) and assumption of a regular symmetrical pattern of facade.

Chapter 2 Automatic identification of window and door regions on mobile LiDAR point cloud

This chapter is devoted to a research paper which has been published in the International Journal of Applied Earth Observation and Geoinformation. The paper covers the methodology details, and the test and evaluation results of the proposed approach of this master's research project. This research paper is authored by Niloufar Haghighatgou as the student, Sylvie Daniel as the director, and Thierry Badard as the co-director of this master's research project. Aside from the numbering of sections, figures, tables, and the reference formatting inside the text, which have been changed to be compliant with the thesis format, the paper has been included in the thesis as submitted to the journal. In addition, in order to avoid content repetitiveness, the reference section of the paper has been removed from this chapter.

Keywords: Mobile LiDAR point cloud, Region growing segmentation, Opening detection, rural building

2.1 Résumé

Étant donné la fréquence élevée et l'impact majeur des inondations, les décideurs ont un besoin urgent de disposer d'outils leur permettant de prédire ou d'évaluer l'impact des inondations sur la population. Les villes numériques 3D qui permettent les simulations d'inondation peuvent fournir une alerte précoce pour les bâtiments qui sont plus à risque pendant une inondation. Comme les ouvertures les plus basses des bâtiments sont plus sujettes à des dommages potentiels pendant l'inondation, il serait nécessaire d'identifier l'emplacement des ouvertures les plus basses des bâtiments, dans le contexte de l'évaluation des risques d'inondation. Les méthodes fréquemment développées dans le domaine de la détection des ouvertures bénéficient de la structure répétitive et de la caractérisation symétrique des ouvertures sur les façades dans les zones urbaines, en plus de la complétude de leurs nuages de points, pour détecter les ouvertures. En revanche, cet article propose une approche globale qui étudie les maisons résidentielles des zones rurales où les ouvertures ont des formes, des tailles et des caractéristiques ou positions non symétriques variées sur la façade, ce qui entraîne l'incompatibilité des méthodes disponibles dans les environnements ruraux. Deux phases, l'extraction de la façade et la détection des ouvertures, sont envisagées pour fournir des boîtes de délimitation autour des ouvertures disponibles sur la façade. Contrairement aux travaux scientifiques précédents, cet article propose une approche de segmentation généralisée dans un contexte impliquant une grande variété de maisons résidentielles avec des structures de façade complexes en présence d'occlusions fréquentes, où la densité des points varie sensiblement d'un bâtiment à l'autre. En proposant un inventaire des défis fréquents liés aux tâches d'extraction de façades et de détection d'ouvertures dans le nuage de points MLS, cet article permet une meilleure compréhension des difficultés pour aider à fournir des solutions plus efficaces et pertinentes dans des contextes résidentiels. Des évaluations qualitatives et quantitatives ont été effectuées à l'aide d'un ensemble de données réelles de la province de Québec, au Canada. Les statistiques ont révélé que l'approche proposée pouvait obtenir de bons taux de performance malgré la complexité du jeu de données, représentatif des données acquises en situation réelle. Les défis concernant les caractéristiques du nuage de points MLS et la présence de grandes occlusions environnantes devraient être étudiés plus en profondeur pour obtenir des informations plus précises concernant les ouvertures sur la façade.

2.2 Abstract

Given the high frequency and major impact of flood events, decision-makers are in urgent need to have tools allowing them to predict or assess the impact of flood events on the population. Digital 3D cities that enable flood simulations can provide early warning for the buildings that are more at risk during a flood. Since building lowest openings are more subject to potential damages during the flood, it would be required to identify the location of the building lowest openings, in the context of flood risk assessment. Frequently developed methods in opening detection domain benefit from the repetitive structure and symmetrical characterization of the openings on the facades in urban areas, in addition to completeness of their point clouds, to detect the openings Conversely, this paper proposed a comprehensive approach that investigates low-rise residential houses of rural areas where openings have various shapes, sizes, and non-symmetrical characteristics or positions on the facade, leading to the incompatibility of available methods in rural environments. Two phases including facade extraction and opening detection are considered to provide bounding boxes around the available openings on the facade. Unlike previous scientific works, this paper proposed a generalized segmentation approach in a context involving a large variety of residential houses with complex facade structures in the presence of frequent occlusions, where the density of the points varies noticeably from one building to another. By proposing an inventory of frequent challenges related to facade extraction and opening detection tasks in MLS point cloud, this paper enables a better understanding of the difficulties to help in providing more efficient and relevant solutions in residential contexts. Qualitative and quantitative evaluations are performed using a real-world dataset of the Quebec Province, Canada. Statistics revealed that the proposed approach could obtain good performance rates despite the complexity of the dataset, representative of the data acquired in real situations. Challenges regarding the characteristics of the MLS point cloud and the presence of large surrounding occlusions should be further investigated for obtaining more accurate opening information on the facade.

2.3 Introduction

This study is a part of a flood risk anticipation project, entitled ORACLE-2, started in 2019 and funded by the Public Security Ministry of the Quebec Province, Canada, to provide comprehensive knowledge of buildings in flood-prone areas including detailed structural and occupational characterization, to better support decision-making at the provincial scale. Accordingly, this research focuses on 3D building facade characterization of residential areas, and it aims at automatic detection of the facade openings, especially the lower ones which are more prone to flood risks, using Mobile Laser Scanning (MLS) dataset. While frequently addressed methods in building characterization domain developed their method on modern buildings (Aijazi et al., 2014; Sun et al., 2020; Vračar et al., 2016), 3D characterization of low-rise residential houses in rural environment that are more vulnerable during flood events are seldom addressed. Unlike modern buildings with repetitive structures of openings, such residential houses present a wide variety of facade structures in which the position and shape of openings are not necessarily consistent as illustrated in Figure 2.1a. In addition, residential houses of such areas often include a basement (Figure 2.1b). Although MLS collects large-scale spatial information, the processing of the resulting point cloud faces several challenges when aiming for the detection of openings, including a) limited reflectivity of the openings, b) presence of occlusions, and c) point density changes.

(a) Different shape and size of the windows (b) Presence of a basement

FIGURE 2.1 – An example of low-rise residential houses

This paper proposes a comprehensive approach that effectively overcomes the abovementioned challenges to detect the available openings of residential houses, with facade structures having no repetitive pattern. As it will be underlined in the forthcoming related studies section, there are few works in the literature dedicated to such context. Despite deep neural networks current preponderance in the facade characterization domain, the context of our research associated with residential houses of towns and rural areas limits the possible solutions to traditional machine learning methods. This is due to unavailability of annotated datasets in rural areas. The proposed approach first performs a segmentation dedicated to facade extraction, using a region growing method adaptive to variation of point density in MLS dataset, considering time-effectivity while retaining accuracy. Second, it employs a facade opening extraction approach, using a hole detection and gridding technique adaptive to MLS datasets.

With this in mind, the next section provides a comprehensive review of the current research exploring building segmentation and opening detection. The proposed approach is explained in section 2.5. Section 2.6 is dedicated to the experimental results and discussion. Finally, some conclusions, a synthesis of our main contributions and direction for future improvements are provided in the last section of the paper.

2.4 Related studies

2.4.1 Building segmentation

Building facade characterization from LiDAR point clouds commonly encompasses two major parts: point cloud segmentation/clustering and facade feature investigation. The prior segmentation of the LiDAR point clouds decreases the processing time and enhances the accuracy of the latter feature extraction task, namely detection of the openings in this research. According to the building which mainly consists of planar structures, plane detection is commonly the first step in segmentation processing. Related methods could be generally categorized into four strategies as: a) clustering, b) energy optimization, c) model fitting, and d) region-growing (Grilli et al., 2017; Rabbani et al., 2006; Wang et al., 2012; Xu et al., 2020; Zolanvari and Laefer, 2016).

Clustering strategies refer to methods that group points sharing common spatial position, geometries, or attributes into primitives by comparing points in a defined neighborhood. The efficiency of the clustering category relies on the selection of calculation criteria and optimal threshold (Xu et al., 2020). Energy optimization strategies that formulate the plane segmentation are frequently used for refinement of the initial segmented plane set (Dong et al., 2018). While being robust to noise and clutter, these methods lead to expensive computational costs (Xu et al., 2020). Random Sample Consensus (RANSAC) (Fischler and Bolles, 1981), and Hough Transform (HT) (Ballard, 1981) methods are two widely used methods in the model fitting category that are being performed in the spatial and parametric domain, respectively. RANSAC groups raw point clouds into segments in which a maximum number of inliers can fit the plane model (Wang et al., 2012; Xie et al., 2020). The method is effective if the facade does not include lots of protrusions and similar details (Zolanvari and Laefer, 2016). HT method, which employs a voting strategy, finds points sharing the same plane by inspecting local maxima in the parametric domain (Vosselman, G , Gorte, B, Sithole, G Rabbani, 2004). RANSAC method proved to be more effective than the HT method (Grilli et al., 2017). Although both methods are generally advised for plane segmentation, the efficiency relies on an acceptable quality of the point cloud, weak noise, and low outliers (Xu et al., 2020).

Region growing methods perform a repetitive process by first getting a seed unit (point, voxel, hybrid) and then inspecting if the neighboring units can join to grow the seed considering the spatial distance and similar properties (Xia and Wang, 2019; Xie et al., 2020; Xu et al., 2020). For the similarity measure, normal vectors, the distance between the growth units, or the combination of these two are being used. (Wang et al., 2011) measured normal vectors of the points based on the neighboring points placed in a 3×3×3 voxel region centered at the point. On the contrary, (Rabbani et al., 2006) considered the k nearest neighbors of the point to calculate the normal vector. By using a fixed number of neighboring points, they adapted the measurement to varying point density since a bigger region was used for points with lower density. For the selection of the seed unit, a common way consists in considering points whose residuals are less than a threshold. The residual of a certain point is calculated by considering a fitting plane on the point and its neighbors (Rabbani et al., 2006; Xie et al., 2020). Owing to their easy implementation, region growing methods are widely used for plan segmentation. However, the effectiveness of such methods depends on the growth criteria and seed unit which needs to be adjustable for the different datasets, especially due to varying point density and outliers (Xie et al., 2020; Xu et al., 2020). This is what is accomplished in the proposed method.

2.4.2 Opening detection

Some opening detection approaches assume that windows hardly reflect the emitted laser pulse to the sensor since windows mainly consist of glass. Thus, holes resulting from limited laser pulses of windows are used to define their location. (Boulaassal et al., 2009; Pu and Vosselman, 2009a) employed long edges of Triangulated Irregular Network (TIN) model for automatic extraction of windows from terrestrial laser scanning data. Points related to the long edges were clustered as the opening boundary points. (Pu and Vosselman, 2009a, 2007) assumed windows either with or without curtains leave holes in the facade wall segment. However, as it will be further discussed in section 2.5.3, points reflected from curtains are sometimes geometrically similar to the points related to the facade, thus being analyzed as being part of it.

(Wang et al., 2012, 2011; Zhou et al., 2018) further investigated hole-based methods to detect windows of a facade using MLS data. The window detection approach proposed a rule-based operator for simultaneous window frame points selection and window crossbar points elimination, in pre-selected facade points Despite the applicability of the approach, the authors simply excluded the ground-floor points (from 10 to 30 percent of the facade's lower part) from the window detection processing since the pattern of the ground floor is different from the rest of the facade. Indeed, there may be a door on the ground floor and different window shapes for which the rule-based operator was not compliant.

Similarly, (Aijazi et al., 2014) detected windows using holes in MLS point cloud. After detection of holes inside the facade as the openings, the proposed method combines symmetrical (repetitive patterns and self-similarities) and temporal (multiple passages) correspondences on the facade to complete the occluded parts of the facade. This method presented successful results by adding temporal correspondence to the processing. (Wang et al., 2016) also relied on the regularities to reconstruct urban facades, including repetitive windows, from point clouds. Likewise, (Li et al., 2018) proposed an approach for corner detection of the repetitive and neatly arranged openings using LiDAR point cloud employing a sliding window to extract the corner points. However, such repetitive patterns and similarities are often not available in residential houses of small towns.

(Zolanvari et al., 2018; Zolanvari and Laefer, 2016) employed a slice-based procedure in addition to a window-hole assumption to extract opening's boundary points from point clouds. The proposed method employs a distance-based analysis along horizontal and vertical slices individually to detect openings of different shape and size. Although presenting promising results, presence of occlusions was not considered as this method used a high-density merged aerial-terrestrial dataset of facade. Another slice-based method is proposed by (Hao et al., 2018) for facade reconstruction of modern buildings. Detection task is conducted considering the assumption of similarity and regularity of the windows in each facade, employing a template-matching method. However, clusters near the highest and lowest elevation values of the wall are removed. This is mainly because the authors believe that in modern buildings, there is no window in these areas of the buildings.

2.5 Proposed approach

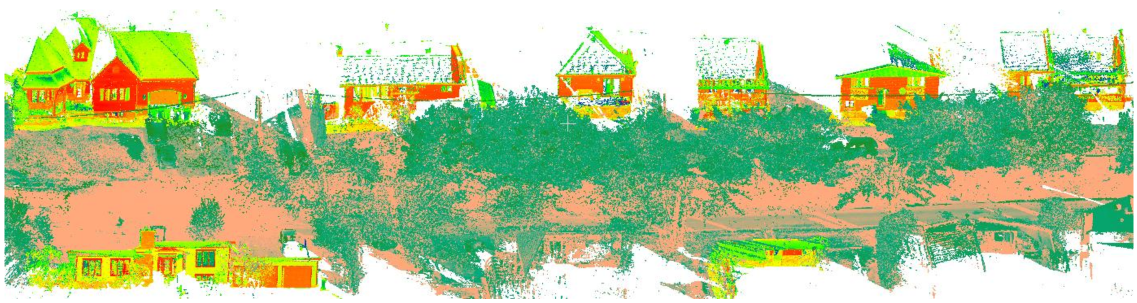
Two major phases consisting of facade extraction and opening detection are considered in the proposed approach to detect the openings of residential houses using an MLS dataset. Although working with a city-scale dataset, the input for the proposed approach is a house sample cropped in the MLS point cloud considering a one-meter buffer around the extruded house footprint. Current developments in the ORACLE-2 project are focusing on building footprints extraction from airborne and satellite images (Badard et al., 2021).

2.5.1 Dataset description

The proposed method has been designed and tested using an MLS dataset of Sainte-Marthe-sur-le-Lac city in Quebec province, Canada, provided by Jakarto Cartographie 3D inc. The mobile mapping unit includes two laser scanners, five 4k cameras, and a localization system, including GPS and IMU. Each laser scanner acquires 2 million 3D measurements per second, with an average scanning speed of 25 km per hour, and with a position accuracy of 2 – 3 cm.

The approximate traveled distanced of the used dataset is 35 km, with the total number of 14 billion 3D points. The point cloud has an approximate point spacing of 1.5 *cm*. *X*, *Y*, and *Z* values, as well as the reflected laser beam intensity are available for each point. According to the available dataset, residential houses in the town have diverse structures and decorations such as staircases with different stair numbers, porch with various shapes and sizes, and several columns. Houses with more complex shapes are also available where facades have different orientation rather than being orthogonal to each other. Figure 2.2 shows an overview of the MLS data coverage and point cloud used in this study.

(a) Top view on Google Earth, Orange: traveled trajectory, Green: bounding box of a representative MLS point cloud



(b) Representative MLS point cloud

FIGURE 2.2 – Overview of the Dataset.

2.5.2 Facade extraction

Two main tasks are addressed in this phase namely, region growing segmentation and facade recognition. Figure 2.3 shows an overview of the detailed processing steps of the first phase.

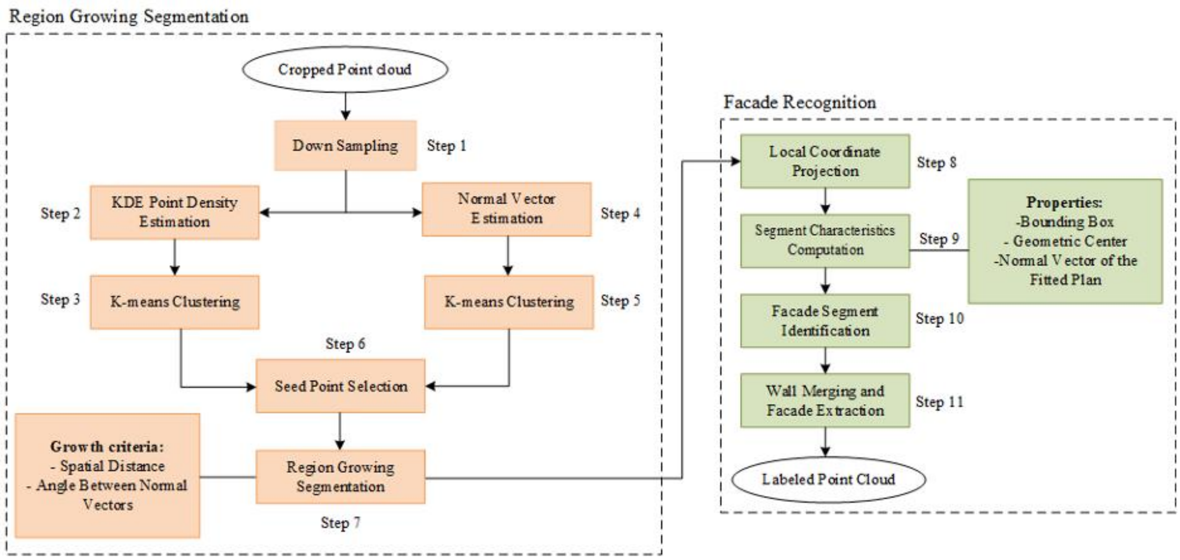


FIGURE 2.3 – LiDAR point cloud processing steps dedicated to the building facade extraction

2.5.2.1 Region growing segmentation

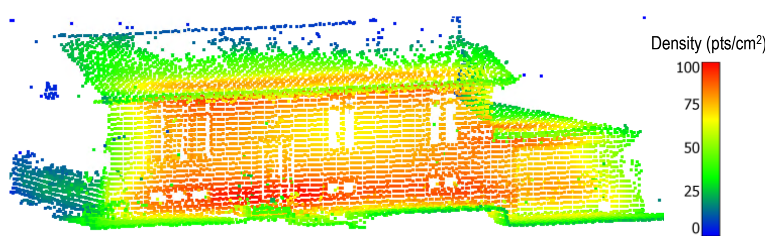
To make the processing time-effective, and make sure the approach is capable of handling point sparsity, the point cloud is down sampled using common voxelization method, with a voxel size of 0.1 - 0.2 m, (Step 1 – Figure 2.3). This voxel size is selected automatically considering the density of the house points with respect to the extent of it (i.e., 3D bounding box around the house points). The region growing method starts with the selection of a seed unit, the seed unit is grown by inspecting the distance and similar properties of each neighboring units, in an iterative process (Xie et al., 2020; Xu et al., 2020). Given the point density variability, these two factors are selected using the Kernel Density Estimation (KDE) (Van Kerm, 2003) to have point density at each point (step 2 – Figure 2.3, Figure 2.4a). Since the point cloud contains at least one totally recorded facade, points with higher density are generally related to the facade wall, making them good seed candidates. However, some entities, such as columns, may have a higher density than the facade walls behind them. To assure having several seed points related to such facade walls, k-means clustering is applied to the estimated point densities to select seeds from points with different density levels (step 3 – Figure 2.3). The number of clusters for the density clustering (n_{kd} in equation (1)) has been determined empirically and set to the optimum number of 150. Moreover, the house may have several parallel or perpendicular walls. Thus, normal vectors of the points in addition to the point density are considered to select the seed points. Relying on a kd-tree structure, the k nearest neighbors of the points are used to assess their normal vectors (step 4 – Figure 2.3). K-means clustering is also applied on the normal vectors to make sure the seed points include a fair diversity regarding the normal vectors, i.e., on both facade sides (step 5 – Figure 2.3, Figure 2.4b). This ensures to get seed points on the side facades even if their walls have a lower point density. The number of clusters for normal vector clustering kn has been determined empirically and set to 3 since there are usually two perpendicular facade sides in addition to roof and ground which are almost parallel to each other while perpendicular to the two facade sides.

Finally in each normal-based cluster, the point with the highest density is selected from all the density-based clusters (step 6 – Figure 2.3). If we consider n_{kd} as the number of clusters in the density-based clustering and kn as the number of clusters in the normal-based clustering, the total number of seed points n_T is:

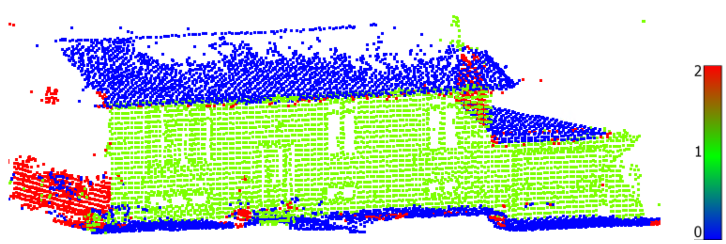
$$n_T = n_{kd} \times kn \tag{1}$$

A higher number of n_{kd} ensures a more reliable selection of seed points, especially for complex cases with more facade decoration, wall attachments, columns, etc. Given the numbers of n_{kd} and kn are equal to 150 and 3 respectively, the number of selected seed points in this study is equal to 450. The number of clusters proved to be the optimum number for all the cases since using greater numbers would not change the result, either for different facade structures or varying distances to the house.

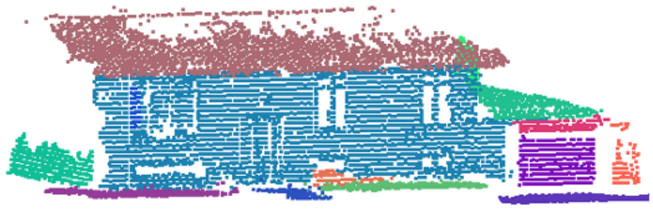
The selected seed points are grown iteratively while the angle between the normal vector of the seed with the selected k nearest adjacent points is lower than a threshold (step 7 – Figure 2.3, Figure 2.4c). The predefined threshold is set to 4° to maintain the accuracy of the region growing. Since segmentation focuses on planar objects (i.e., facade walls), we considered the coplanarity criterion sufficient for growing the region.



(a) Point density estimation – step 2. Color bar values are normalized. Red color demonstrates higher percentage of point density while blue color demonstrates lower percentage of point density



(b) K-means clustering of normal vectors – step 4,5. The number of clusters for normal vector clustering kn has 3 absolute values in range [0, 2]



(c) Region growing segmentation – step 7. Random colors are assigned to the segments

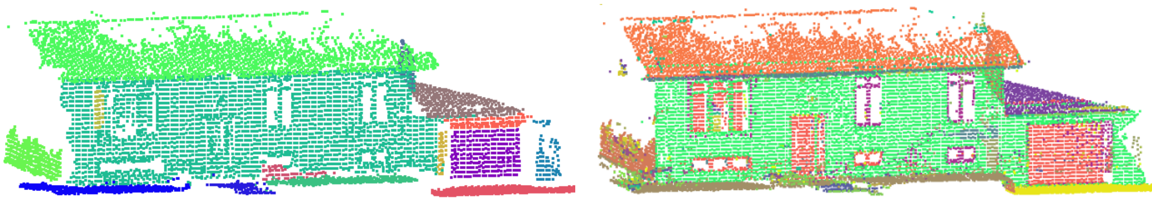
FIGURE 2.4 – Region growing segmentation task

2.5.2.2 Comparison with existing methods

Comparisons were made with approaches that have been commonly employed for the task of building segmentation, namely basic region growing (Rabbani et al., 2006) and planar RANSAC-based (Boulaassal et al., 2007) approaches. As the proposed approach uses down sample point clouds, all houses were down sampled with the same voxel size to include comparable results. Similarly, the same parameters were used as the proposed approach, namely: the normal angle threshold for the region growing-based approach was set to 4°; the distance-to-plane threshold of the RANSAC-based approach was set to 5 *cm*. The basic region growing used point residuals to the fitted plane for selecting the seed points.

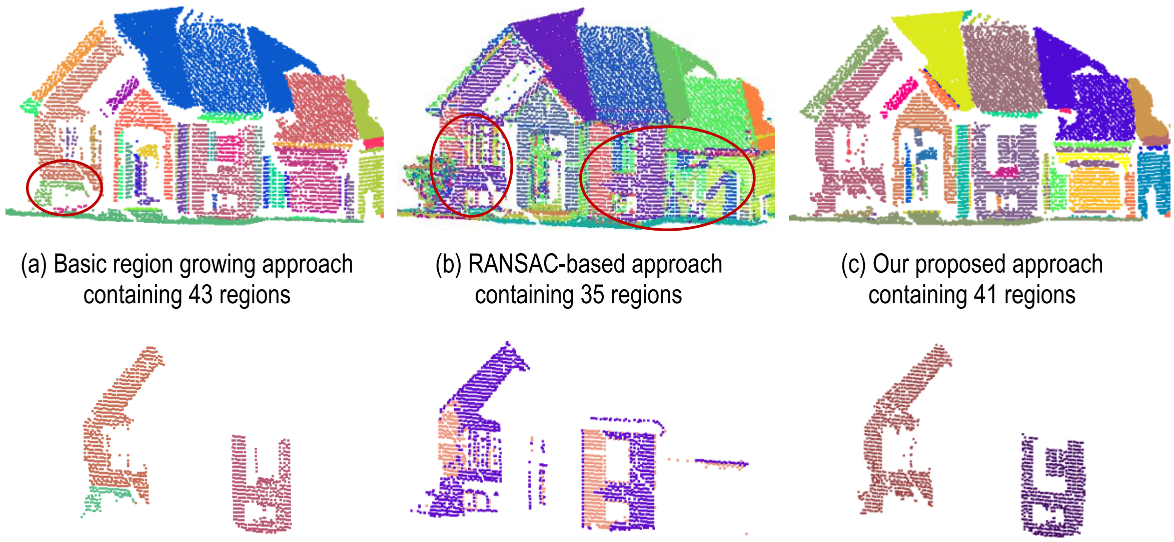
A first comparison was conducted involving the house with a simple structure. Figure 2.5 presents the segmentation results of the two basic methods. Having a more homogeneous result, the basic region growing approach reached a better segmentation result than the RANSAC approach which is noisier. Moreover, for this simple case, the result of the region growing approach is almost the same as our segmentation approach (Figure 2.4c), which is not surprising since both rely on the same principles and have been set up with corresponding parameters.

A second comparison was conducted involving a house with a complex structure, containing rapid depth differences of parallel facade walls. Figure 2.6 shows the segmentation results for our proposed approach and the two basic methods. This example reveals the outperformance of the region growing-based approaches (Figure 2.6a, c) rather than the RANSAC approach (Figure 2.6b). RANSAC yields over-segmentation of the point cloud. To better underline this issue, Figure 2.6e shows two extracted segments related to the facade walls where the RANSAC incorrectly merged several points of the left wall into the right wall and reverse. The basic region growing segmentation also achieved good results while a small portion of the left wall was grouped as a separated segment. However, our adaptive segmentation approach could correctly segment these two walls (Figure 2.6f). It has been also observed that the performance of the RANSAC approach noticeably depends on the point density of the house, which might result in over- or under-segmentation. Moreover, for this complex case, our proposed segmentation approach, using seed points based on the point density (Figure 2.6c), outperformed the basic region growing, that selects seed points using the point residuals.



(a) Basic region growing approach containing 15 regions (b) RANSAC-based approach containing 22 regions

FIGURE 2.5 – Comparison of the segmentation step for a house with simple building structure.



(a) Basic region growing approach containing 43 regions

(b) RANSAC-based approach containing 35 regions

(c) Our proposed approach containing 41 regions

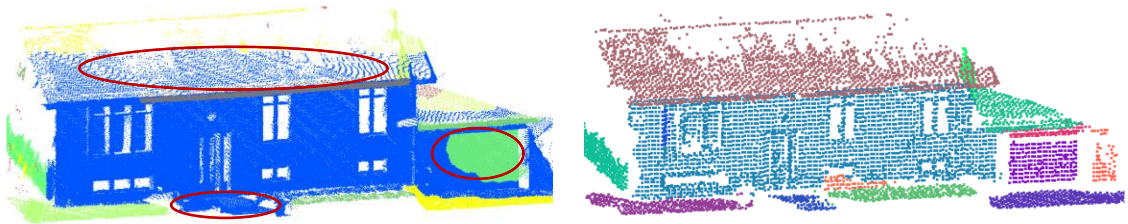
(d) Extracted segments of facade related to (a)

(e) Extracted segments of facade related to (b)

(f) Extracted segments of facade related to (c)

FIGURE 2.6 – Comparison of the segmentation step for a house with complex building structure.

A comparison was further conducted with a recently developed approach based on the RANSAC method considering a graph-cut structured optimization dedicated to urban areas (Guinard et al., 2019). As shown in Figure 2.7a**,** this RANSAC-based approach resulted in under-segmentation in several parts of the house that led to include parts of the roof and porch in the facade segments. In addition, the rightest area of the facade is placed in a different segment. However, more consistent segments could be seen in our result (Figure 2.7b). Although being further improved with respect to the original RANSAC, this comparison revealed that method (Guinard et al., 2019) or similar approaches could not be applied in datasets where the house structures vary from simple to complex. Moreover, this comparison confirmed that the proposed adaptive region growing could outperform more complex ones while being applicable to wide variety of situations.



(a) RANSAC-based approach (b) Our approach using down sampled point cloud

FIGURE 2.7 – Comparison of our adaptive region growing approach with a RANSAC-based approach of (Guinard et al., 2019).

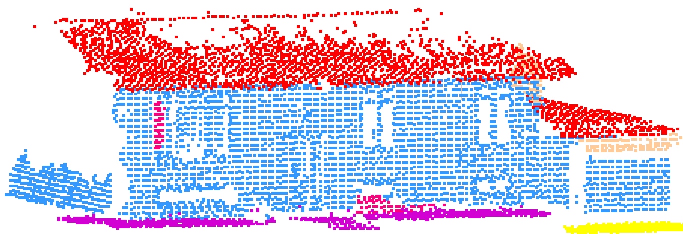
2.5.2.3 Facade recognition

Extraction of the facade is performed based on the general geometrical and topological characteristics of the building entities such as the roof is always placed above the facades. The following series of entities were considered: main-wall (M), basement-wall (B), roof (R), porch (P), decoration (D), and ground (G), as well as unclassified (U). Moreover, three geometrical characteristics of the segments are considered to identify the entity they relate to, namely their size, position, and alignment using 3D bounding box, geometric center, and normal vector of the fitted plane, respectively (step 9 – Figure 2.3). The recognition process is carried out using the combination of these three characteristics computed for each segment (step 10 – Figure 2.3, Figure 2.8a). A series of conditions are defined to identify the six entities of interest, as shown in Table 2.1. A class label representative of one of the six entities is assigned to each segment.

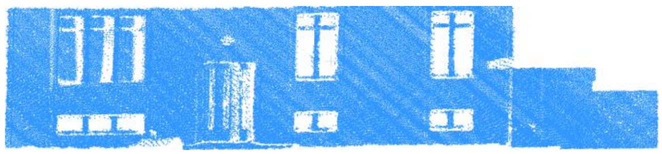
Table 2.1 Defined conditions for identifying the six entities of interest

	Size	***Position***	***Alignment***
Main wall	Relatively large	Middle	Vertical – parallel to z axis
Roof	Relatively large	Highest	Oblique
Basement wall	Equal or smaller than main wall/roof	Upper than ground – lower than main wall/porch	Vertical – parallel to z axis
Porch	Smaller than Main wall/roof	Upper than ground – lower than facade wall	Horizontal – perpendicular to z axis
Ground	Relatively large	Lowest	Horizontal – perpendicular to z axis
Facade decoration	Relatively small	No condition	No condition

Finally, by comparing the distance between extracted wall segment in combination with their alignment, we determine if two neighboring segments are related to the same facade wall or two facade sides (step 11 – Figure 2.3, Figure 2.8b). Additionally, to retain the available level of detail of the facade wall, all the possible points inside the 3D bounding box of the extracted facade are retrieved considering the similarity of the points' normal vectors with respect to the normal vector of fitted plane to the segment. More specifically, for each voxel located in the facade bounding box, all points inside that voxel that have the same normal vector as the facade, are retrieved and considered as the facade points. This way, we keep the original point density of the data for later steps.



(a) Facade segment identification – step 10. Color coded rendering represent six entities of interest



(b) Facade extraction – step 11. All the points inside the bounding box of extracted facade are retrieved to the original density of the point cloud

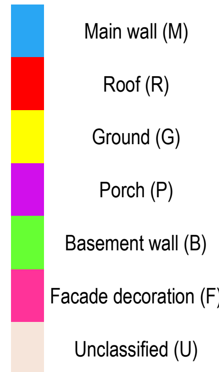


FIGURE 2.8 – Facade recognition task

2.5.3 Opening detection

The second phase performs the extraction of holes. The purpose is to isolate regions of the facade that could be either the facade's opening or occlusions in the vicinity of the house. Dedicated processing steps are currently being developed to discriminate holes related to openings and occlusions, which are not included in the current paper. Figure 2.9 shows an overview of the detailed processing steps of the second phase.

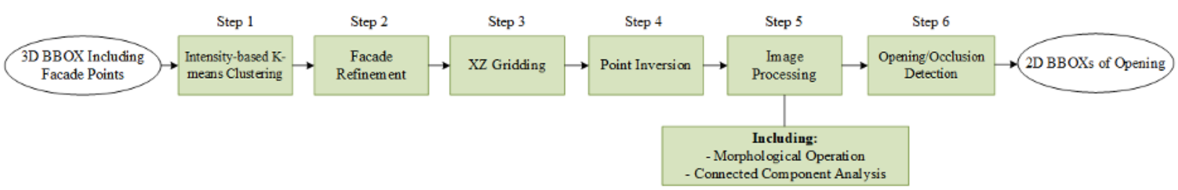
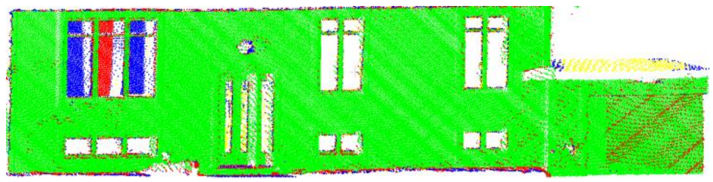
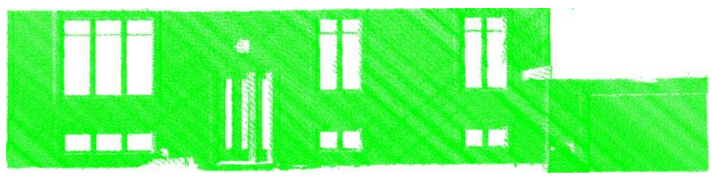


FIGURE 2.9 – LiDAR point cloud processing steps dedicated to the opening detection

While each available facade has been extracted, a lot of unrelated points may still exist among the facade points. This inevitable issue occurs mainly due to the presence of curtains very close to the facade wall. As a result, the assumption of hole detection would not work in such a case. Accordingly, points inside the extracted facade bounding box still need to be clustered to separate and remove the points related to the curtains. While geometrically similar, the intensity range of the points related to the wall proved to be different enough to be distinguished from the points related to the curtains. Therefore, the whole point cloud of the house is first clustered using the intensity values (step 1 – Figure 2.9). Then inside the bounding box of the extracted facade, the points related to the cluster with the greater number of points are extracted as the refined facade wall since, in general, the number of points related to the wall is significantly greater than the number of points related to other clusters, such as window crossbars, curtains, etc. (step 2 – Figure 2.9, Figure 2.10).



(a) Rendering of the points based on the intensity-based clustering of the house, Random colors are assigned to the clusters



(b) Refined facade points considering the cluster with the greatest number of the points

FIGURE 2.10 – Refinement of the extracted facade using k-means clustering of the intensity values

As explained in section 2.4.2, the slice-based opening detection method (Zolanvari and Laefer, 2016) was effective in terms of detecting openings of different shapes and sizes. The proposed approach relies on a similar principle. However, both vertical and horizontal slices are considered at the same time. A surface similar to a Digital Terrain Model (DTM) is created, using points not in the XY plane, but in the XZ plane instead (step 3 – Figure 2.9). Like DTM generation, this step 2, hereinafter referred to as XZ gridding, leads to a two-dimensional (2D) raster of the refined extracted facade. For the XZ gridding resolution cell, different values were tested, and the value of 3 cm proved to be working for various houses since the average distance between the points in our dataset is 1.5 cm. Since the holes inside the facade need to be investigated for opening detection, rather than the points related to the facade wall itself, a point inversion (Aijazi et al., 2014) was then applied inside the raster (step 4 – Figure 2.9, Figure, 2.11). This means that *True* value is assigned to cells having previously *False* value (holes cells), and conversely, *False* value is assigned to cell having previously *True* value (wall cells).

FIGURE 2.11 – *XZ* gridding and point inversion

Finally, the proposed approach consists in applying series of image processing techniques to extract the openings/occlusions (step 5 and 6 – Figure 2.9). Morphological operations with relevant structuring elements are first applied to the raster to remove small objects. Connected components are then extracted and analyzed to find if there still exist any obvious irrelevant components. Bounding boxes are finally extracted around the location of the detected openings/occlusions on the facade (Figure 2.12). As the scope of this research is to help determining the elevation of the lowest opening, topological analyses could be applied considering the location of detected openings' bounding boxes, as well as the height of the previously labeled segments (porch, ground, basement wall, etc.). Finally, using the DTM (which has been built from ground points), the elevation of the bottom point of the lowest opening (i.e., lowest edge of the detected opening's bounding box) with respect to the ground could be obtained.

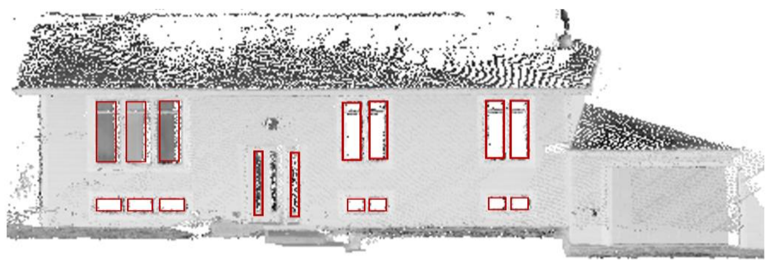


FIGURE 2.12 – Bounding boxes of the final detected openings/occlusions superimposed on the original point cloud

2.6 Results and discussion

2.6.1 Performance criteria

To validate the performance of the proposed approach, 22 sample residential houses with total number of 67 facade sides have been selected. Dedicated criteria and assessment have been considered for each phase. The experiments were tested and evaluated using a computer with 8 GB RAM and Intel Core i7- 3770 @ 3.40GHz CPU.

2.6.1.1 Facade extraction

To assess the performance of the facade extraction phase, residential houses are classified into two categories including simple to moderate (SM) and moderate to complex (MC) classes. These categories were considered in terms of four characteristics of the facade walls, described in Table 2.2.

Table 2.2 Categorization of residential houses

	Characteristics			
	Wall Quantity	***Point density***	***Occlusion***	***Diversity***
SM	– One or two perpendicular facade walls	– Dense point cloud	Small surrounding objects: Bins, low vegetations, chairs, etc.	– Without column and facade decorations – Simple structured facade walls, porch, and stairs
MC	– More than two perpendicular/parallel facade walls in different depth – More than two faced walls with oblique alignment	– Sparse point cloud, mostly due to tall trees and vegetation, self-occlusion by long terrace's walls	– Big surrounding objects: Tall trees, cars, dense bushes, etc. – Self-occlusion: outdoor parking's walls, columns, long terrace's walls	– With several column, and terraces – Complex structured facade walls, porch, and stairs with staircase

Accordingly, a qualitative assessment criterion is considered to label each of the extracted facade walls as being either correctly, partially correctly, or incorrectly segmented. A correctly and incorrectly segmented facade wall means a true positive and a false positive, respectively. A partially correctly segmented wall refers to a wall which was clustered into several segments during the region growing process (step 7 – Figure 2.3) while not all of these segments are identified as main wall segments in the identification process (step 10 – Figure 2.3). This assessment relies only on a detection basis, not on the geometry and surface of the walls.

2.6.1.2 Opening/occlusion detection

For the performance evaluation of the second phase, a two-stage assessment is considered involving a manually selected ground truth. The recall and precision metrics (Xu et al., 2020), usually involved as object detection metrics, are used to compare the 2D polygons of the ground truth with the detected openings/holes polygons. These metrics are calculated from true-positive (TF), false-positive (FP), and false-negative (FN), using equations (2) and (3). To be considered as a true positive, as the first-stage assessment, the distance between the geometric center of corresponding pair needs to be lower than the predefined threshold (15 cm in this study, which is consistent with the smallest acceptable opening' hole). In addition, as the second-stage assessment, the minimum overlap between the convex hull polygons of the detected openings/holes (W_D) and the corresponding ground truth (W_R) using Intersection over Union (IoU) metric is required (75% in this study). This combination of distance-based and surface-based analyses provide a better assessment specially for complex cases containing openings with curtain or openings impacted by an occlusion.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

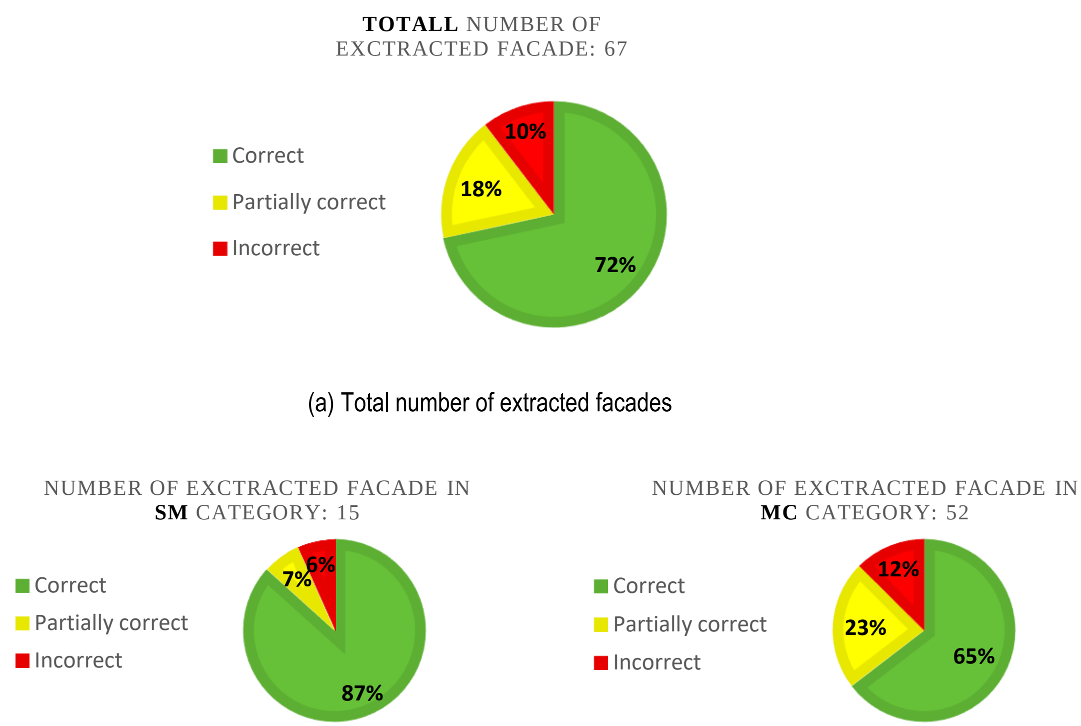
$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$IoU = \frac{W_D \cap W_R}{W_D \cup W_R} \tag{4}$$

2.6.2 Performance analysis

2.6.2.1 Facade extraction

Results of the facade extraction phase were evaluated in terms of the defined qualitative criteria. Results in Figure 2.13a underlines the approach good performance while using a diversity of residential houses. Among the 67 total number of the extracted facade, 72% of the facade walls are fully segmented and correctly identified, while 18% of them could partially be identified. Likewise, as illustrated in Figure 2.13b and 2.13c, analyses reveal that for SM, the proposed method could obtain fairly good results. Partial or misidentification mostly occurred for MC samples. It is worth noting that most of the samples were rather complex cases. Three of which are presented in Figures 2.14-2.16.



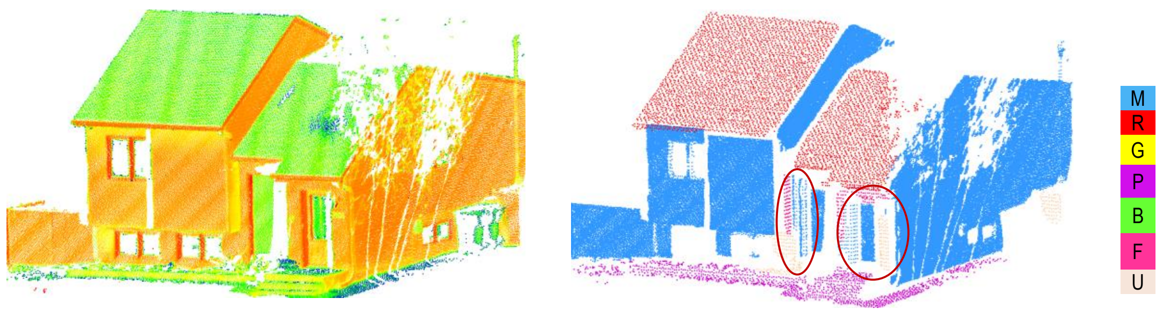
(a) Total number of extracted facades

(b) Number of extracted facades in SM category

(c) Number of extracted facades in MC category

FIGURE 2.13 – Performance assessment of the facade extraction phase

Despite this good performance, there are still issues that need to be further improved. Figure 2.14 shows one of them where small segments on the right side of the front facade were mistakenly labeled as decoration (pink color) and unclassified (beige color). This is due to the segment small size in combination with rapid depth differences, causing a wall to be over-segmented during the region growing step. Figure 2.15 shows another example of incorrect wall identification, where the house contains several facade walls which are not located along a perpendicular alignment, but with smaller angles with respect to each other. However, given the opening detection goal, having more correct facade walls at the cost of having more incorrect extraction should be favored. The last complex example (Figure 2.16) shows dense vegetation located very close to the facade, resulting in an absence of points at this location leading to an incomplete extraction of the facade wall.



(a) Intensity rendering of the original point cloud

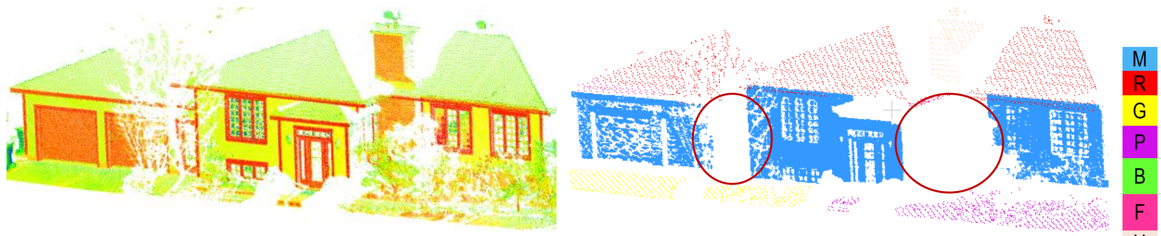
(b) Result of the facade extraction phase

FIGURE 2.14 – An example of a complex case representing the misidentification of some facade wall segments due to their size and depth differences

(a) Intensity rendering of the original point cloud

(b) Result of the facade extraction phase

FIGURE 2.15 – An example of a complex case representing the incorrect extraction due to the similar characteristics of facade



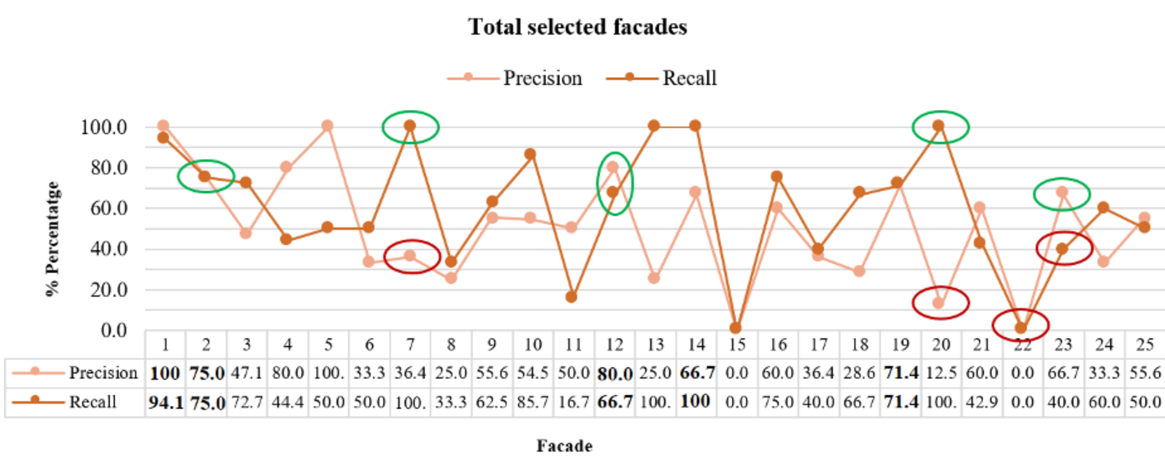
(a) Intensity rendering of the original point cloud (b) Result of the facade extraction phase

FIGURE 2.16 – An example of a complex case representing the partial facade extraction due to the presence of vegetation very close to the facade

2.6.2.2 Opening/occlusion detection

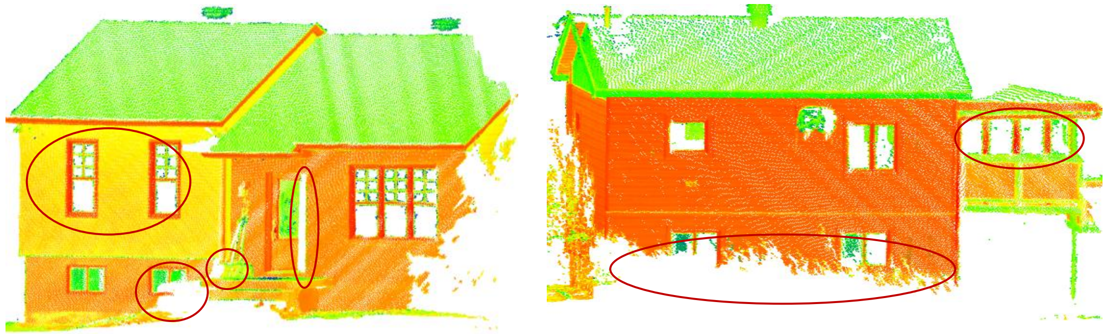
In the following, only 25 out of the 67 facade sides of the 22 sample houses are used. Some facades were removed since the openings were not even visible for the human operator or there was no opening. In addition, facade walls with depth differences, that were previously considered separately in the gridding process, were considered as belonging to the same facade. Figure 2.15 shows an example where the number of extracted facade walls is equal to 4 while during the second phase it is reduced to 2.

The precision and recall metrics of the opening detection phase are provided in Figure 2.17. There are five samples for which performances are satisfactory (i.e., almost equal, or greater than 70%). Figure 2.18 shows two of these samples (facades number 2, 12 – Figure 2.17). The precision and recall of facade number 2 are both equal to 75% despite self-occlusion, objects in the vicinity, and two types of wall material. The precision and recall of facade number 12 are equal to 80% and 66.7% respectively despite occlusions and holes related to terrace's attachments and decoration.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Precision	**100**	**75.0**	47.1	80.0	100.	33.3	36.4	25.0	55.6	54.5	50.0	**80.0**	25.0	**66.7**	0.0	60.0	36.4	28.6	**71.4**	12.5	60.0	0.0	66.7	33.3	55.6
Recall	**94.1**	**75.0**	72.7	44.4	50.0	50.0	100.	33.3	62.5	85.7	16.7	**66.7**	100.	**100**	0.0	75.0	40.0	66.7	**71.4**	100.	42.9	0.0	40.0	60.0	50.0

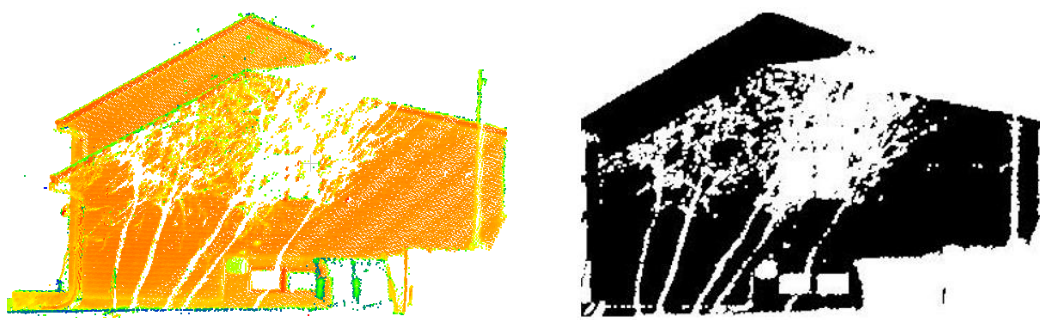
FIGURE 2.17 – Performance assessment of the opening detection phase for the selected facades individually. Green and red circles express high and low performances, respectively



(a) Example 1, facade No. 2 (b) Example 2, facade No. 12

FIGURE 2.18 – Two intensity rendering examples of houses with high performance where signs of self-occlusions, small surrounding objects and changes of wall materials exist

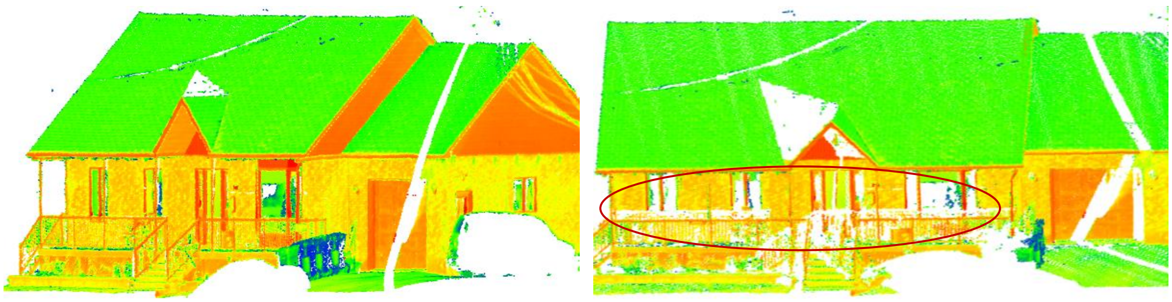
There are several falloffs in both precision and recall performances. They mostly result from occlusions leading to either higher rate of false positives (occlusion holes having characteristics similar to opening hole) or false negatives (occlusion holes merged with opening holes). In Figure 2.19, the low performance occurs due to high rate of false positives (facade number 20 – Figure 2.17). This house contains two windows on the lower facade area. Moreover, a tall tree is also visible nearby inducing a lot of small holes, i.e., connected components inside the facade wall. Thus, several of these false candidates were selected as the openings due to their similar characteristics with the small opening holes. The precision for this facade is equal to 12.5% (2 TP and 14 FP), while the recall is 100% since opening holes are truly detected (2 FP and 0 FN).



(a) Intensity rendering of the original point cloud (b) XZ gridding result

FIGURE 2.19 – An example of an incomplete point cloud involving large occlusion due to the vegetation, resulting in high FP and low precision

In Figure 2.20, low performances occurred due to both high FN and FP rates, and more specifically no TP detection. Consequently, both recall and precision values are equal to zero (facade number 22 – Figure 2.17). This is due to big self-occlusions. Figure 2.20a shows the original point cloud according to the viewing angle of the MLS system, while Figure 2.20b shows the same point cloud from the front view. As it can be seen, a big portion of the facade (including windows) is missing. This hole having an approximate length equal to that of the facade wall is removed during the connected component analysis while all opening holes were also merged with it.

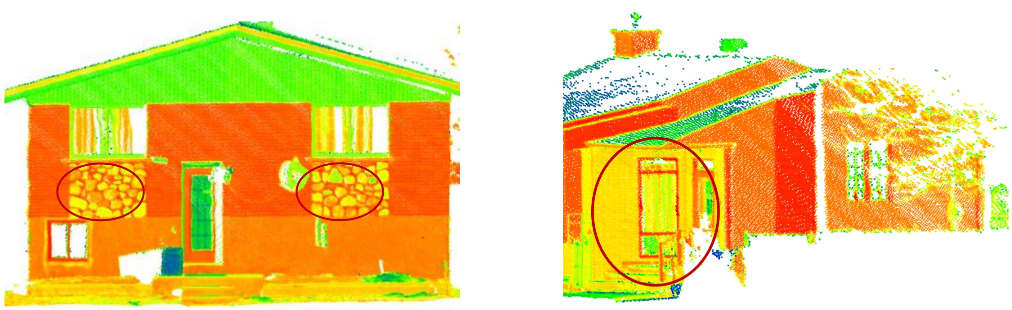


(a) Original point cloud with approximate viewing angle of the MLS system

(b) Original point cloud with frontal view

FIGURE 2.20 – Example of an incomplete point cloud showing self-occluded facade portion, resulting in low performance

So far, we observed how occlusions impact the performance of the detection system. However, this is worth noting that real-word datasets dedicated to production use, such as in this research, always contains such imperfections. Moreover, the performances are impacted by changing in the material of the facade walls. Figure 2.21a shows an example where the changes in walls' material led to FP detection. In Figure 2.21b, such changes resulted in FN detection (facade number 7, 23, respectively – Figure 2.17).

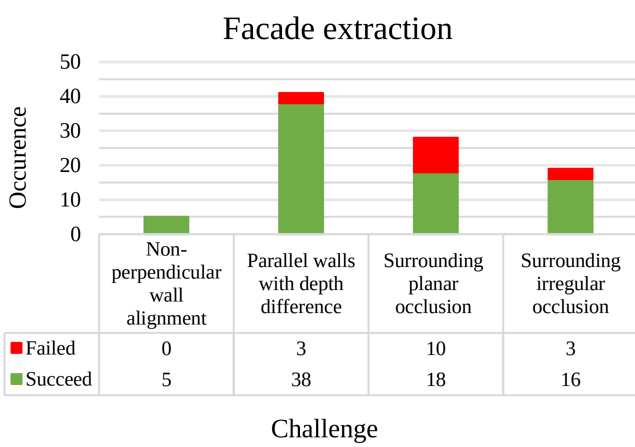


(a) Example yielding high FP rate

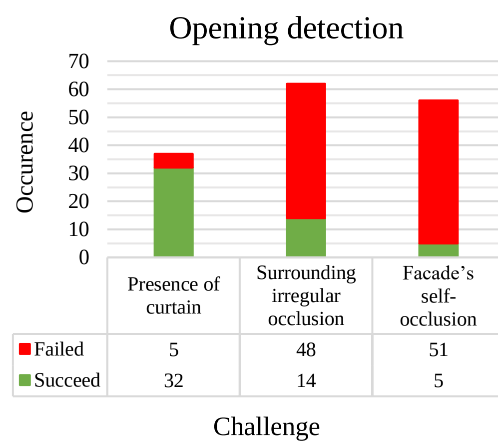
(b) Example yielding high FN rate

FIGURE 2.21 – Two examples of houses containing different wall materials

To further discuss the solution issues, an inventory of challenges is provided in Figure 2.22 for each phase individually. This inventory counts the occurrence of available challenges resulting either in success or failure using the proposed approach. For the first phase (Figure 2.22a) four types of common issues were identified, among which the complex facade structures and surrounding occlusions are the two most frequent. However, they have gained less attention in the literature. Despite such challenges, the proposed approach obtained good performance. For the second phase (Figure 2.22b), three types of common issues were identified. The total number of the occurrence reveals the frequency of these challenges and more specifically, the complexity of the real-world MLS dataset. If we consider the total number of openings (W_R) for all 25 selected facades, namely 162, the occurrence of occlusions (self-occlusions and surrounding) occurred 103 times. This emphasizes the necessity of either providing complementary datasets or designing dedicated processing to overcome occlusions for obtaining better results, especially for the production uses. Moreover, this inventory demonstrates the effectiveness of the intensity value to reduce the effect of the opening curtains since out of the 37 occurrences, 32 were processed successfully.



(a) Inventory of the first phase: facade extraction



(b) Inventory of the second phase: opening detection

FIGURE 2.22 – Inventory of common challenges of the MLS dataset

2.7 Conclusion

This paper proposed an automatic approach to detect the available openings of residential houses using the MLS point cloud considering no assumption regarding the facade's repetitive structure or symmetrical characterization. While region growing is highly sensitive to the selection of the seeds and growing criteria, the proposed approach efficiently adapted the facade segmentation to various houses and made it possible to automatically segment MLS point cloud of rural residential context with varying point densities and diverse facade structures. The qualitative assessment of the first phase revealed that the proposed approach could obtain promising results. The proposed approach thus proved to be efficient, with respect to the desired specifications. Nevertheless, some areas for improvement have been identified. The opening detection phase employed a hole-based approach combined with a gridding technique to detect the 2D bounding boxes of openings of various shapes and sizes. By successfully eliminating the points related to the curtains or window crossbars, the proposed approach led to a more consistent characterization of openings. The quantitative assessment of the second phase showed that the proposed approach could achieve an acceptable performance rate and is robust to opening variation as long as points are available on the facade.

This is worth noting that out of the total number of the selected residential houses, more than half of the cases were characterized as complex. This reveals the real-world characteristics of MLS datasets which usually receive less attention in the literature. Indeed, assuming the completeness of such point clouds often lead to the inapplicability of developed approaches for production use where complete datasets are not usually available. To help specifying the characteristics of a dataset to be representative of real-world point clouds, we proposed, as a contribution of this research, an inventory of the frequently available challenges both for extraction and detection phases.

In future work, a third phase will be considered in order to distinguish the openings from the occlusions using shape regularity and the occurrence of points inside the house (Zou and Sester, 2021). We foresee the benefit of the proposed approach while using UAV-based LiDAR point clouds since it is robust as long as points related to the openings are available. We also envision the use of the proposed approach to label MLS point cloud of rural areas given the current preponderance of deep neural network solutions but the lack of annotated datasets compliant with our study context.

2.8 Acknowledgment

This work was supported by the Quebec government [CPS 18-19-17] with a financial contribution of $ 1,035,000, through the ORACLE-2 project conducted at Laval University for the Ministry of Public Safety. The authors would like to thank Jakarto Cartographie 3D inc. Québec, Canada, for providing the MLS dataset of Sainte-Marthe-Sur-Le-Lac used in this work.

2.10 Complements to the paper

This section presents updates of the proposed approach that have been considered after the submission of the paper. It first addresses the discrimination of the holes related to real openings versus holes resulting from occlusions. Afterward, given the purpose of the ORACLE-2 project, it covers an approach to extract building's first floor and the lowest opening, as well as their elevation.

2.10.1 Update of the approach to discriminate opening from occlusion

The current output of the proposed approach is a set of 2D bounding boxes of the facade openings of a residential house. However, a functional method allowing discrimination of real openings from occlusion is still missing. Due to the time allocated to this master's research project, this issue, identified in the document as phase 3, has not been completely addressed and is still in progress. Recent advances are described below.

As it has been pointed in the literature review chapter, the existence of occlusion in urban areas has remained a constant challenge for building characterization approaches. Unlike dedicated strategies in the literature that commonly benefit from regularity and repetitive facade structure, residential houses in small cities barely represent such characteristics. Therefore, in this research, two assumptions were previously considered to detect the occlusions. The first one concerns the occurrence of points in the vicinity of openings. In LiDAR data of urban areas, few points may exist inside the houses since laser beam can penetrate through the window and acquire points from inside the house, i.e., voyeur effect (Tuttas and Stilla, 2013). As the result, the occurrence of the points after the hole, inside the house, would be a sign of a window. On the contrary, when a hole is the result of an occlusion, points should exist for the corresponding object. As the result, the occurrence of the points in front of the hole, outside the house would be a sign of an occlusion. The second assumption concerns opening's shape regularity.

In order to examine the first assumption of point occurrence, similar to recent approaches of (Voelsen et al., 2021; Zou and Sester, 2021), a ray tracing algorithm can be applied. By considering if the emitted laser beam either hit an object located in front of the facade or not, the ray tracing approach discriminates holes resulting from occlusions from real openings. A similar concept was also employed by (Bénitez et al., 2010) using LiDAR point cloud to enhance the facade reconstruction conducted by means of images. As for the second assumption, the experiments conducted in the second phase of the project have shown data imperfections and occlusions can be severe and significant. In this context, the assumption of shape regularity of the extracted openings proved to be no longer valid. Therefore, to retain the generalization of the approach, only the assumption of the point occurrence by means of the ray tracing algorithm is further considered to discriminate the openings from occlusions.

The ray tracing approach proposed in this research consists of the following steps. Points that are labeled as facade, in addition to all unlabeled points in front of the facade, are considered for investigation in a 3D voxelized space. Given each emitted laser beam intersects a voxel from each MLS station, all the voxel stores an occupancy status for each beam at each location. The available MLS system trajectory of the used dataset, as shown in Figure 2.23, is employed to determine the beam station and its direction to each voxel. The occupancy status can have two labels of miss, when a beam traverses the voxel, or hit, when a beam hit a point in the voxel, which leads to the following:

- Unlabeled voxel (point) and hit status (beam not traversed): occlusion
- Unlabeled voxel (point) and miss status (beam traversed): opening
- Labeled voxel (point): facade

Finally, holes related to detected occlusions are excluded and the remaining holes are considered as the openings.

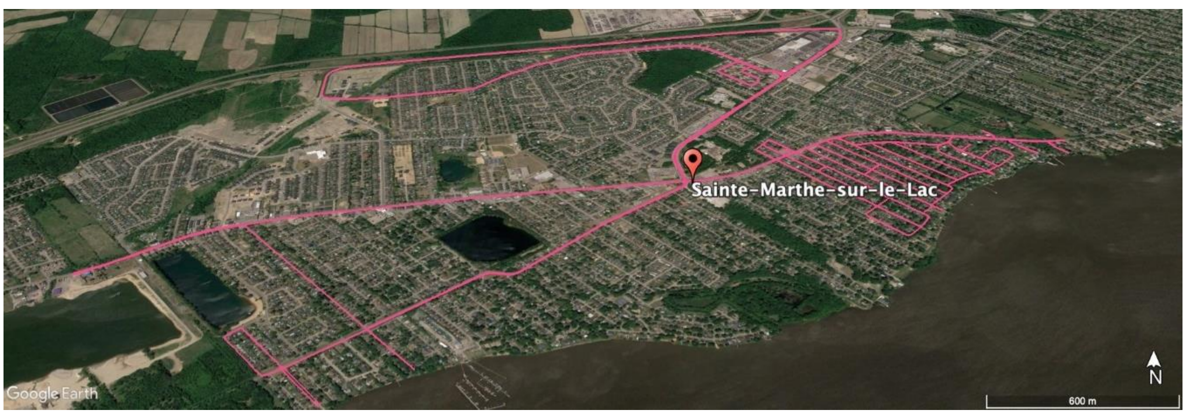


FIGURE 2.23 – Overview of the dataset area including MLS system trajectory (pink)

Similar to the previous phases, the implementation of the occlusion detection phase is being developed using python programming. These developments are still at an early stage. While there exists no dedicated python library for ray tracing, a few libraries are available which could be further generalized to be implemented in our context, including VTK and Point Cloud Library (PCL). VTK tool includes ray casting algorithms through pyCaster module (Hanwell et al., 2015; Schroeder and Martin, 2018), which is of interest. The algorithm has been mainly developed for retrieving the intersecting points between a ray and a surface mesh.

PCL library includes occlusion estimation in a voxelized space through VoxelGridOcclusionEstimation class (Amanatides and Woo, 1987). Originally developed in C++, it has been specifically developed to find the object that would be first hit by the ray during data acquisition, i.e., foreground occlusions in our context. While the python binding for this class has not been developed yet, it will be generalized in our context to be used in python, to be compatible with the rest of the processing environment in this research. It should be noted that voxel size is of great importance. If a very small voxel size is selected, there would be many unoccupied voxels in front of the house, i.e., the casted ray would not intersect the voxel (point) but traverse it and would result in miss status. On the contrary, if it is very big, the scene would not be correctly represented and several misdetections, i.e., hit status would occur. This issue may even get heightened due to point density changes of the MLS dataset. As mentioned in the data description section, the average point spacing of the used MLS data is 1.5 *cm*. Accordingly, tests and trials should be conducted to experimentally select a voxel size applicable to the characteristics of our used dataset.

2.10.2 First floor and lowest opening extraction

As previously mentioned, the objective of this research is to detect openings on the facade by focusing on the lowest ones, in order to be able to determine more precisely the elevation of the first floor as well as the bottom point of the lowest opening (i.e., purpose of the ORACLE-2 project). With such structural elevations of the buildings, during a flooding episode, it is possible to know whether the water only enters through the lowest opening and floods the basement, or the first floor would be also damaged, resulting in the building's total loss and causing severe damage costs.

To do this, the first floor and the lowest opening should be first determined and then, the elevation could be estimated. Figure 2.24 shows an example of a house point cloud in which all segments are labeled, and the possible openings have also been detected. Accordingly, the lowest detected opening is first determined by considering the elevation of the extracted 2D bounding boxes associated with openings (black rectangles). Then, based on a concept similar to that of the segment identification process (step 10 - Figure 2.3), a topological analysis can be applied to determine the location of the first floor, taking into account the general knowledge of residential houses in Quebec (e.g., the first floor intersects the porch; it is at most two meters above average ground level; it is also higher than the basement wall, if applicable). Detailed explanations of such an analysis are provided in the paper. The identified building features that can be used in this step are mainly: the porch, the basement wall, the lowest point of the available facade sides, and the ground, and their associated properties such as the elevation of their lowest point and their positions. Finally, the Digital Terrain Model (DTM) is taken into account to find the elevation of the first floor and the bottom point of the lowest opening with respect to the ground.

It should be noted that due to the wide variety of facade structures in the province of Quebec, a wide range of topological conditions must be considered in order to maintain the generalizability of the proposed approach.

This issue requires a complete detection of all the lowest openings to be able to develop such a generalized elevation extraction. In addition, to ensure that the first floor and the lowest opening are correctly extracted, all facades of the residence must be available.

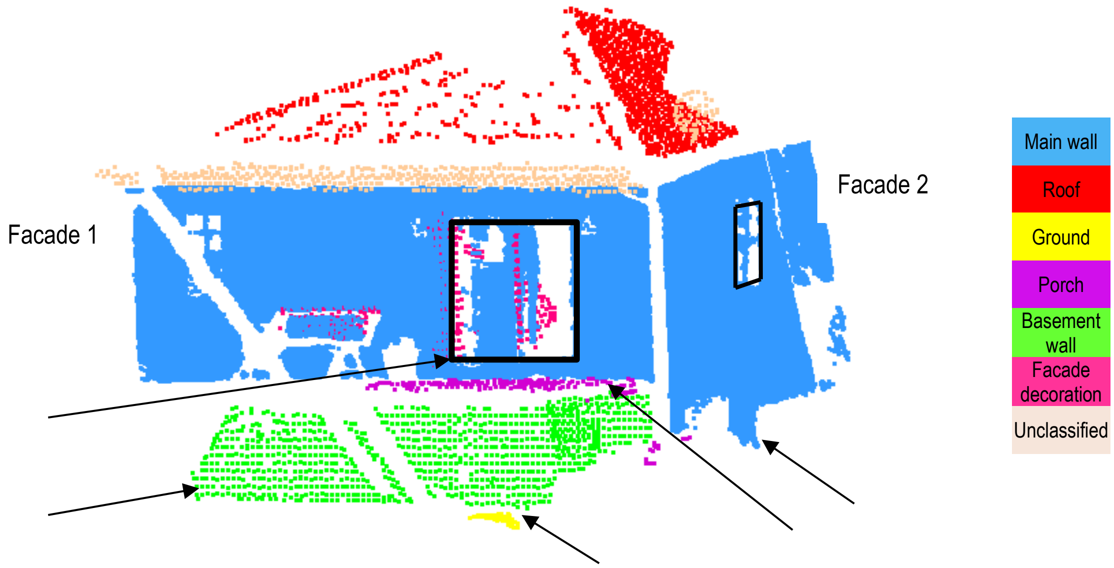


FIGURE 2.24 – An example of the segmented house showing the types of information related to the first floor and lowest opening extraction using topological analysis. Black rectangles show 2D bounding boxes of the detected openings, and black arrows are pointing to building entities that could be used in this analysis.

For the evaluation of the accuracy of the relative elevation, respectively, at the first floor and the lowest opening, it is necessary to have a reference measurement. For this purpose, similar information acquired from traditional surveying techniques should be made available.

In general, in ideal situations where there are no signs of occlusion in front of the house and the openings have been fully scanned by the MLS, the accuracy obtained for the elevation of either the first floor or the lowest opening is about 3 cm, which is consistent with the quality of the datasets provided by the MSP project. However, for cases where the openings are partially occluded, especially the lower parts, the accuracy is reduced and conditional on the visibility of the points and features to be extracted.

Conclusions and Perspectives

Conclusions

The general objective of this research was to design and develop a fully automatic opening detection approach of residential houses using an MLS dataset. The targeted approach had to be able to detect openings with different shapes and sizes from point clouds with varying point densities. This objective was aligned with the purpose of the ORACLE-2 project, which aimed at providing the height information of the lowest opening as well as the first floor for the sake of flood-risk anticipation. The main objective of this research was divided into three specific objectives.

The first specific objective was to design and develop a segmentation approach, dedicated to facade extraction. While region growing is highly sensitive to the selection of the seeds and growing criteria, the proposed approach efficiently adapted this method to various houses and made it possible to automatically segment MLS point cloud of rural residential context with varying point densities and diverse facade structures. As the comparison of the proposed approach with a recent research work revealed, despite being successful in urban complex scenes, the RANSAC-optimization-based method failed to successfully segment a simple residential house due to the lower density of some of the building entities (such as a roof) with respect to others (such as main facade wall). Following the adaptive region growing approach, employing the knowledge-based facade identification using topological and geometrical characteristics of the residential houses led to successful extraction of the facades, from simple cases to very complex ones. The proposed approach thus proved to be efficient, with respect to the desired specifications. Nevertheless, some areas for improvement have been identified. Thus, although having easy implementation, the region growing approach is not effective in terms of computational time and would need to be optimized. In addition, further tests including additional topological/geometrical criteria would be required to generalize the approach to a wider context. Also, the presence of planar foreground object, especially combined with the existence of complex facade structure (i.e., walls with different alignment including perpendicular, non-perpendicular, parallel but with depth differences) results in low performance. Such issue should be addressed.

The second objective was to design and develop an opening extraction approach, applicable to the opening of different shapes, sizes, and contexts. Given the prior successful wall extraction, the proposed approach of the second phase performed the detection of the opening in 2D space. Using the relevant cell resolution applicable to various cases, this 2D conversion resulted in an automatic, easy, consistent, and time-effective detection of the holes on the facade. In addition, the second phase could eliminate the points related to the curtains or window crossbars, leading to a more consistent characterization of openings. More specifically it allowed a more robust detection of the opening relying on intensity range differences between the facade wall and the above-mentioned points. The proposed approach used the k-means clustering to eliminate these unrelated points from the facade. However, there have been cases where the use of intensity in such an unsupervised manner led to elimination of wall portions (i.e., false holes) and further false detection of the openings. A more accurate assessment of the clustering or an alternative solution should be investigated to improve the clustering result and prevent such misdetection. The quantitative assessment of the second phase revealed that the proposed approach was effective as long as the facade points were available, no matter the density of the points. However, as soon as occlusions, which were mainly vegetation and facade self-occlusions, existed close to the facade, this issue would decrease the performance of the proposed approach.

The third objective, aiming to design a hole recognition approach to discriminate holes related to openings from holes related to occlusions, is still in progress due to the time allocated to this master's degree. Two assumptions regarding a) shape regularity, and b) point occurrence have been considered. While the former is not applicable to point cloud with data imperfection, it is still useful for opening type (door/window) discrimination when occlusion does not occur. In such context, shape regularity will be assessed using different relevant shape descriptors. The latter will be addressed using ray-tracing technique that has recently shown promise in a similar context. In addition, openings partially hidden by vegetation will be detected using a similarity criterion related to the shape and size of windows located on the same building level.

An MLS point cloud of Sainte-Marth-Sur-le-Lac city in Quebec province, provided by Jakarto cartographie 3D Inc. was used in this research project. Although being one of the most accurate types of data, the use of MLS LiDAR point cloud in residential context led to the conclusion that the completeness of such data type (i.e., presence of occlusions) highly affects the performance, especially for the detection task. Moreover, it allowed a better understanding of the real-world data characteristics, compared to rather ideal datasets that have been frequently used in other research works.

To assess the performance of the proposed approach, the qualitative assessment of the first phase has been performed by means of visual validation, and the quantitative assessment of the second phase has been conducted employing the ground truths that had been manually generated. However, a better assessment of the proposed approach could be achieved using more accurate ground truth.

Contributions

The proposed approach contributes to MLS point cloud segmentation of residential context where the density of the points varies noticeably from one building to another, or even inside an individual building. Previous scientific works have rarely addressed a generalized segmentation approach in such a context involving a large variety of residential houses with complex facade structures (including adjacent parallel walls of different depth and non-perpendicular alignments) in the presence of frequent occlusions (including self-occlusions such as columns or terraces, and surrounding objects). The originality of this work relies on various components, like the density-based seed selection and clustering in the region growing and the LiDAR intensity clustering in the opening detection. The latter has proven to be particularly effective for opening covered with curtains. To our knowledge, there is no previous research work that employed the intensity of the points for the opening detection task.

Another contribution of this research work is an inventory of usual challenges related to facade extraction and opening detection tasks using MLS point clouds in residential areas. To our knowledge, such inventories have not been previously provided in other research works. The availability of such inventory can help designing efficient and relevant solutions. It can provide better knowledge to build an open dataset for such segmentation and detection tasks in the residential context. Moreover, it can provide a better understanding of the main differences between such datasets and public datasets that are currently being used in the residential context.

Finally, this research contributed to a paper published in the International Journal of Applied Earth Observation and Geoinformation. As provided in chapter 2, this paper includes the detailed knowledge and theoretical aspects of the proposed approach, the practical processing steps using a representative dataset, as well as an explicit discussion of the challenges and performance, in terms of approach and the employed data, making it a good reference for future studies in similar contexts.

Future works and perspectives

As previously explained, the house sample would be automatically cropped in the MLS point cloud considering a one-meter buffer around the extruded house footprint. This automated selection is assumed to be achieved using the building footprint extraction approach designed and developed in the ORACLE-2 project. However, the sample selection has been conducted manually at the moment. Thus, the early future work will be to use the footprint dataset to automatically crop the house sample to better assess the full automation of the proposed approach.

Given the main purpose of the ORACLE-2 project is to extract the elevation, future work will be focusing on conducting experiments to assess the precision of the first floor and the lowest opening elevations that can be obtained by means of the proposed approach. To this purpose, similar information acquired from more accurate techniques such as traditional surveying will be required as the ground truth.

As extensively discussed in chapter two, low performances mostly resulted from the imperfection of the MLS data. Such imperfections are mostly due to the presence of occlusions, mainly self-occlusions and vegetation.

Although this information has not been available to us at the moment, using RGB colorized point cloud could be advantageous, especially for the opening detection task. We have already observed how the intensity value could differentiate the points related to the curtain from the points related to the facade wall in an unsupervised manner. Relying on the same concepts using the RGB information of the window borders with respect to the other facade points should be investigated.

Since the proposed approach proved to be robust as long as points related to the openings are available, we anticipate the applicability of the proposed approach in the context of LiDAR point clouds acquired with UAVs, given its ability to adapt to point density variations. Due to its viewing angle, UAV point clouds of residential areas would have less occlusion and would allow the extraction of openings on all facade sides.

We also envision the use of the proposed approach to label point clouds acquired with mobile LiDAR systems in rural areas given the current preponderance of deep neural network solutions but the lack of annotated datasets consistent with our study context.

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