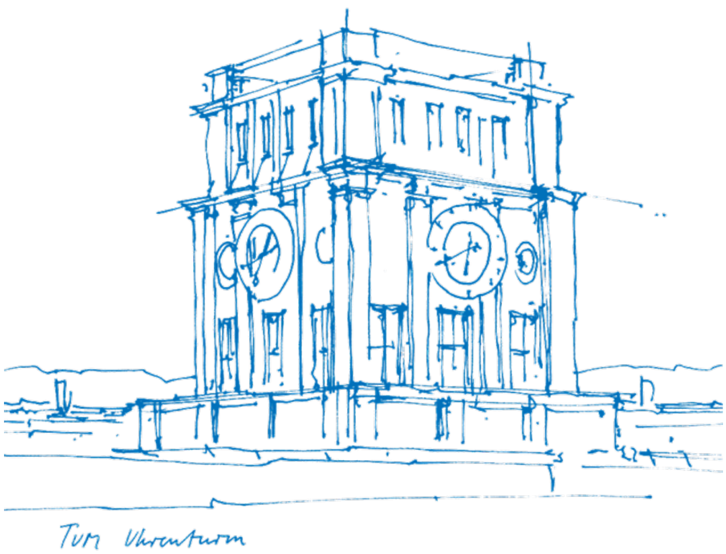
Photogrammetrie und Fernerkundung
TUM School of Engineering and Design
Technical University of Munich

3D Cities: Evaluating 3D building reconstruction tools using point clouds

Bachelor's Thesis

Chenhao Huang



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Chenhao Huang

Thesis for the attainment of the academic degree

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at the TUM School of Engineering and Design of the Technical University of Munich.

Examiner:
Prof. Dr.-Ing. Boris Jutzi

Supervisor:
M.Sc. Olaf Wysocki

Submitted:
Munich, 01.09.2024

I hereby declare that this thesis is entirely the result of my own work except where otherwise indicated. I have only used the resources given in the list of references.
I also declare that I used ChatGPT for spelling and grammar checks. However, the content and arguments presented in this thesis are entirely my own work.

Munich, 01.09.2024

Chenhao Huang

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Abstract

This thesis evaluates the efficacy of 3D building reconstruction tools through point cloud data, focusing on their accuracy, efficiency, and scalability in urban modeling contexts. The research employs an in-depth comparative analysis of Airborne Laser Scanning (ALS) and Mobile Laser Scanning (MLS) technologies to create models of different Level of Detail(LoD). It assesses the capabilities of tools such as 3dfier[1]and Polyfit[2], integrating these advanced scanning technologies with a robust testing framework to measure performance and investigate the interoperability of ALS and MLS data to enhance model precision and utility. The analysis delves into the processing pipelines of each tool, highlighting their strengths and weaknesses in managing the complex data typical of urban environments. Findings reveal significant variations in tool performance, influenced by data characteristics and specific modeling requirements. These insights not only guide targeted improvements in tool functionalities but also establish best practices for digital urban modeling.

Contents

1 Introduction

1.1 Motivation

In the context of rapid global urbanization, buildings form the core of urban structures and play a crucial role in urban ecosystems. As climate change introduces unprecedented challenges such as rising sea levels, intensified heat island effects, and increased frequency of extreme weather events, urban planners are increasingly turning to advanced technologies for effective response strategies. High-precision three-dimensional (3D) building models have become essential, offering extensive applications in climate-related analysis. These models enable planners and decision-makers to thoroughly assess the environmental impacts of building designs, optimize energy usage, and enhance urban resilience. Additionally, they provide unique value in various specific scenarios, aiding in the tailored application of urban planning strategies.

These 3D city models also have practical applications across various fields. For instance, Level of Detail 2 (LoD2) models can accurately measure solar exposure in urban settings, supporting the planning of large-scale green energy projects. This is vital for advancing sustainable urban energy initiatives, including solar energy deployment[3]. Moreover, these models help simulate urban noise, aiding in the scientific assessment and design of quieter, more harmonious urban environments, such as around wind farms and pumping stations.

The creation and updating of these models depend heavily on point cloud data, a detailed format captured through methods such as terrestrial laser scanning, aerial photogrammetry, and drone technology. Despite providing rich geospatial information, point cloud data poses challenges in building high-quality 3D models, including managing large datasets, ensuring algorithm accuracy and efficiency, and enabling real-time model updates.

In the navigation field, the application of 3D city models is equally significant. For instance, Amap (Gaode Maps) uses these models to calculate building shadows, thereby offering pedestrians and cyclists the best routes to avoid direct sunlight[4]. This feature is especially popular during hot summer days, providing a more comfortable outdoor experience and showcasing the practical uses of 3D building models in daily life.

Although existing 3D building reconstruction tools offer some solutions, improvements are still required in terms of accuracy, efficiency, and the ability to handle large-scale point cloud data. This study is conducted to evaluate the performance of various 3D building reconstruction tools, with a particular focus on their accuracy, efficiency, and scalability. The capability of these tools to process different types of point cloud data will be assessed, identifying their strengths and weaknesses, and providing recommendations based on specific Level of Detail 2 requirements. Through the application of these tools to datasets and subsequent analysis, a deeper understanding of each tool's performance characteristics will be gained, providing a scientific basis for further development and application of 3D building models.

1.2 Study Aims

This project aims to critically evaluate the performance of two automated 3D reconstruction software tools, 3dfier[1] and Polyfit[2], using Airborne Laser Scanning (ALS) and Mobile Laser Scanning (MLS) as primary data sources. By referencing the Level of Detail 2 (LoD2) models from Geoportal Bayern as the ground truth, the study seeks to explore the effectiveness of these tools in processing different types of point cloud data and their ability to achieve varying degrees of modeling precision. The objectives include investigating the operational workflows of the software, identifying potential challenges within experimental procedures, and quantifying the accuracy and reliability of the generated models in comparison to established benchmarks. This comprehensive assessment aims to delineate the strengths and limitations of each tool, offering insights that could guide future improvements and applications in the field of urban modeling and architectural reconstruction.

2 State of the Art

Current research explores various 3D reconstruction methods, with a particular focus on the use of small commercial drones as reconstruction platforms[5]. These drones offer significant advantages due to their compact size and versatility, allowing them to maneuver into areas that are difficult to reach with conventional methods and collect more precise point cloud data from closer distances. This enhances the data foundation for subsequent modeling processes and achieves an exceptionally low RMSE (Root Mean Square Error) of 0.015m[6], representing a level of precision superior to traditional total stations, tacheometry, and traversing. Drones also exhibit a higher degree of freedom and efficiency in data collection, further enhancing their value in 3D reconstruction efforts.

However, the limited battery capacity of general rotor quadcopters poses a significant challenge for large-scale urban scanning projects. Commercially available drones with laser scanners have very limited flight endurance, requiring battery replacement at least every half hour, necessitating equipment restarts. While adequate for small-scale projects, this is unsuitable for extensive urban surveys. Additionally, drone usage regulations in many countries impose further restrictions, especially on large, long-endurance drones, often prohibited in urban areas. Consequently, the feasibility of using drones for laser scanning is significantly limited, with ALS (Airborne Laser Scanning) or MLS (Mobile Laser Scanning) remaining the primary sources for point cloud data in current research.

In contrast, Airborne Laser Scanning (ALS) is widely used for large urban and geospatial data collection projects because of its strong performance, wide area coverage, and efficient scanning[7]. Mounted on airplanes or helicopters, ALS uses pulse lidar technology to quickly gather large-scale data, covering extensive areas in just a few hours. This rapid data collection leads to accurate Digital Terrain Models (DTMs) and Digital Surface Models (DSMs), made possible through efficient, automated processing[8]. Although ALS's typical point cloud density of about 10 cm might not match the finer detail achievable with drones (UAVs), it is fully adequate for most urban planning and construction efforts, even if it may not meet the extremely high precision required for intricate engineering surveys or detailed cultural heritage documentation.

ALS's capability to quickly scan large areas is essential for large urban projects, effectively capturing the layout of city terrain and buildings which is vital for early design decisions and planning. Its continuous data collection during flight significantly boosts operational efficiency by gathering large amounts of data in one go, eliminating the need for frequent stops to change batteries or equipment. Additionally, ALS systems are equipped with advanced data processing software that manages large volumes of point cloud data. This software improves data usability and accuracy through noise reduction, data filtering, and model enhancements.

Given its ability to provide detailed information that supports city-level planning and decision-making, ALS is the best choice for extensive spatial data collection. By balancing cost, efficiency, and accuracy, ALS is crucial in modern urban modeling and geoinformation science, particularly effective in scenarios requiring long-term, wide-area, and high-accuracy surveys.

Transitioning from airborne to ground-based laser scanning, Terrestrial Laser Scanning (TLS) stands out as an essential technique[9]. As a traditional method, TLS generates point cloud data by emitting laser pulses and capturing the reflections[10]. This process yields highly precise three-dimensional data, useful in Building Information Modeling (BIM) and Heritage Building Information Modeling (HBIM)[11]. Beyond architectural and cultural heritage applications, TLS is versatile enough for geological tasks like terrain analysis and rock slope stability assessments, showcasing its wide applicability.

However, TLS comes with challenges and limitations in practical use. Primarily, TLS equipment is expensive, and processing the scan data typically requires specialized software, which can significantly raise project costs. Moreover, scanning complex structures often requires multiple scanning stations to cover all angles, adding complexity to data processing and increasing both time and financial costs.

In terms of architectural modeling, while TLS provides highly precise data, its cost and operational complexity may make it impractical for large-scale projects or those that do not require high precision. Additionally, the extensive and detailed point cloud data generated by TLS demands robust computing resources and expertise for effective processing and analysis. Integrating data from multiple scanning locations also presents challenges, as it requires accurate site calibration and point cloud registration techniques to ensure precision. Moreover, in areas with dense construction or complex terrain, TLS might not capture all necessary data from one position. Often, multiple angles and locations are needed to complete the data set, further complicating the project.

Considering these factors, although TLS offers unparalleled advantages in many areas, its cost-effectiveness and suitability must be carefully evaluated before implementation. For small-scale or precision-critical projects, TLS is a powerful tool, but for larger or cost-sensitive projects, more economical alternatives might be necessary. In this context, Mobile Laser Scanning (MLS) technology has gained popularity in modern urban planning and building reconstruction due to its efficient data collection capabilities and precise modeling results[12]. Unlike Airborne Laser Scanning (ALS) and drones (UAVs), MLS employs high-performance laser scanners mounted on ground vehicles, allowing for detailed point cloud data collection while navigating through city streets[13]. This approach provides an intricate view of building facades and structures close to the ground, effectively filling the gap between ALS's expansive aerial coverage and the granular, street-level insights provided by MLS.

MLS excels in capturing the detailed contours of urban "canyons" or areas flanked by high buildings, offering denser point cloud data than ALS due to its proximity to the targets. Additionally, MLS's advanced scanning instruments generally produce higher quality point cloud data compared to UAVs. However, MLS has limitations such as a smaller coverage area and susceptibility to ground obstacles, which can make it difficult to capture complete profiles of rooftops and buildings. This restricts its application in large areas or along densely built streets. On the other hand, ALS, although slightly less dense in point cloud data, can quickly cover extensive areas, making it ideal for large-scale terrain and building mapping, thus showing its strengths in broader urban planning contexts.

In many advanced urban planning and geographic information system applications, 3D building model reconstruction is a crucial technical field.Through the application of several point cloud processing methods, precise 3D urban models may be obtained from diverse data sources including LiDAR, photogrammetry, UAVs, and others. These techniques are continuously evolving, propelled by the complex nature of urban environments and advancements in data collection technology. This evolution has led to the development of innovative building reconstruction methods that not only increase efficiency but also effectively address the detailed requirements of contemporary applications.

Existing software solutions such as 3dfier, employ a technique based on building footprints to involve point cloud data directly onto predetermined ground planes to reconstruct fundamental architectural models. This procedure usually entails utilising point cloud data to create roof structures, which are subsequently synchronised with the building's height data and footprint to formulate models that adhere to Level of Detail 1 (LoD1) criteria. While this approach efficiently utilizes existing ground plane data to simplify the modeling of complex structures, it may not capture all vertical structural details and roof structures.

Unlike 3dfier, which generates only a single-plane roof, City3D[14] employs a more complex method by projecting multiple planes onto the building footprint. It uses a technique similar to 2.5D Dual Contouring[15], first reconstructing a building's structural framework and then adding the roof structure. City3D enhances the reconstruction of building structures beyond what 3dfier offers, upgrading the model from LoD1 to LoD2. On the other hand, Polyfit does not rely on building footprints. Instead, it directly extracts planes from the existing point cloud data and calculates the optimal combination of these planes to reconstruct the building's LoD2 model.

A comparative analysis of these technologies enables the selection of the most appropriate modeling approach according to the specific requirements of a project. Additionally, it facilitates a more profound comprehension of the strengths and limitations of each technology, so promoting the progress and use of 3D architectural modeling technologies.

1. 3D Modeling Based on Building Footprints and LiDAR Point Clouds

One common approach involves using building footprints and LiDAR point cloud data to generate three-dimensional building models. The approach outlined here initially utilises two-dimensional building footprints to determine the basic size and layout of buildings. Furthermore, the elevation data obtained from LiDAR is projected onto these footprints[1]. This procedure efficiently produces the initial shape of the buildings, and subsequent refinement of the roofs and facades of the structures is achieved through further processing. One key advantage of this method is its capacity to create basic forms of the building models for large urban area while ensuring alignment with actual geographical coordinates.

2. Multi-View Stereo (MVS) Technology

In some cases, particularly in urban environments, photos taken from multiple angles can be used to generate 3D models. Multi-view stereo technology enables the reconstruction of 3D models from overlapping images[16]. This approach detects common characteristic points in several images and utilizes their geometric correlations to compute their locations in three-dimensional space, therefore generating very precise 3D visual representations. This approach becomes particularly advantageous in settings where conventional LiDAR scanning is not feasible.

3. Adaptive Mesh Reconstruction Technology This technique dynamically adjusts the size and shape of the mesh to better match the density and complexity of the point cloud data. In processing building point clouds, this method can effectively capture detailed features of buildings, such as windows, doors, and decorative moldings. Adaptive mesh adjustment helps optimize the use of computational resources and improves the overall quality and accuracy of the model[17].

4. Semantic Segmentation and 3D Modeling Integration In recent years, there has been a considerable growth in the use of deep learning methods for image and point cloud processing. Utilizing semantic segmentation on point clouds enables the identification of distinct components of structures, including walls, roofs, and grounds[18]. Furthermore, utilizing this semantic information to direct the 3D modeling process not only boosts the precision of the models but also amplifies their visual authenticity. This approach is especially well-suited for the automation of extensive 3D urban model reconstruction, yielding substantial enhancements in both work productivity and accuracy.

5. Closed Plane Analysis and Modeling When dealing with complex architectural structures, especially those with intricate roof structures, closed plane analysis technology can effectively reconstruct 3D models of buildings. The 3D shape and interior structure of buildings can be automatically inferred by examining the relationships and connecting structures of the planes in the point cloud[19]. In addition to architectural modeling, this technique finds application in industrial design and cultural heritage preservation.

Combining these technologies allows for the efficient reconstruction of detailed and accurate 3D architectural models from a range of data sources. In addition to having excellent visual accuracy, these models can be used for historical research, contemporary urban planning, and environmental monitoring. Future building rebuilding efforts will be more precise and productive as technology and algorithm optimizations develop.

3 Methodology

3.1 Workflow Overview

The workflow of how the buildings are reconstructed can be seen in Figure 3.1. This workflow is used to evaluate the reconstructing results of 3dfier and Polyfit.

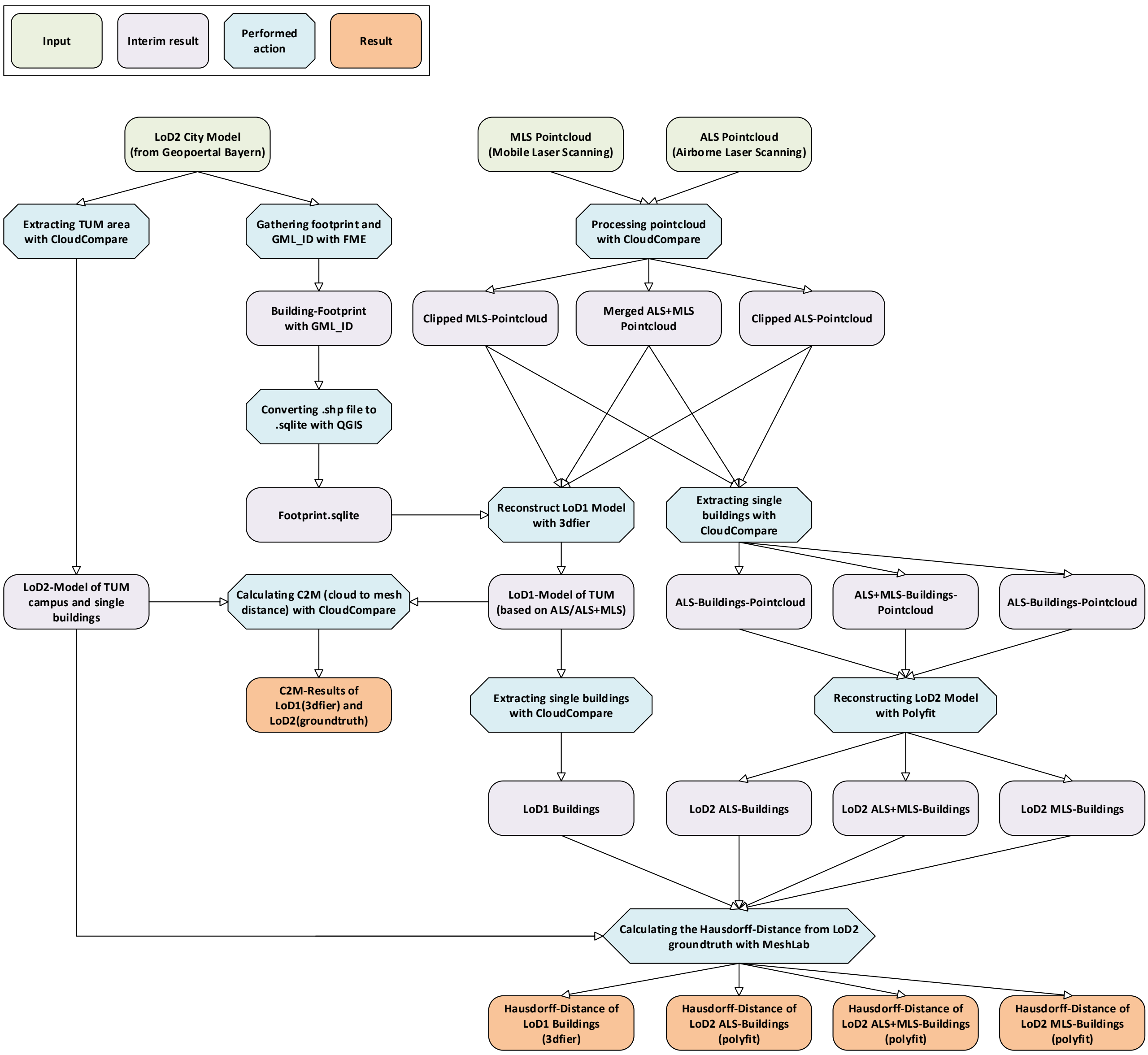

Figure 3.1 Workflow

The project is divided into two parallel part. The first is reconstructing LoD1 models based on 3dfier. It is an open-source software developed by TU-Delft(Delft University of Technology), is specifically designed for the automated reconstruction of urban 3D models. This software mainly uses building footprints and point cloud data for 3D reconstruction, projecting the point cloud onto the footprint to achieve LoD1 models.

This method is particularly suitable for constructing urban models for environmental simulations, such as noise, wind, air pollution, and temperature simulations. The second part is to reconstruct LoD2 buildings by Polyfit. It is an advanced framework developed by Visual Computing Center from KAUST(King Abdullah University of Science and Technology), is designed for reconstructing lightweight polygonal surfaces from point clouds. Polyfit addresses the challenge of creating accurate 3D models from point clouds that may contain noise, be incomplete, or exhibit other imperfections.

3.2 3dfier:

3dfier is engineered to streamline the creation of simple 3D models. This tool processes 2D GIS datasets, such as topographical maps, converting them into 3D by the process known as "3dfication," which gives the datasets a three-dimensional form. It utilizes elevation data extracted from a point cloud, presently compatible with LAS/LAZ formats. The system harnesses the semantic attributes of each polygon to elevate and refine the model. To construct a watertight digital surface model (DSM) that incorporates 3D objects, 3dfier seamlessly integrates the polygons by stitching them according to predefined rules to close any elevation gaps. The software employs a rule-based structure to extrude water features as horizontal polygons, generate LoD1 blocks for buildings, smooth out road surfaces, and construct bridges with 3D polygonal surfaces.

The key working principle of 3dfier is converting 2D geographic datasets (such as terrain datasets) into 3D models through a "3Dification" process. This process includes the following key steps:

1. Input Data Processings: The input 2D polygon data, representing buildings, lakes, roads, etc., usually comes from open datasets such as OpenStreetMap. Additionally, elevation points obtained using laser scanners (typically stored in LAS format) or derived from aerial images are also used for modeling.

2. Geographic Semantic Uplift: The software performs a 3D uplift using the semantic information of the input polygons. For example, water body polygons are uplifted to horizontal polygons, buildings to prismatic blocks, and roads to smooth surfaces. After each polygon is uplifted, adjacent polygons are "stitched" together to form a unified surface without gaps.

3. Output and Optimization: The output 3D dataset is semantic, tagged based on the input polygons(footprint), and optimized for use in different software, supporting multiple output formats including international standards such as CityGML.

3dfier is implemented based on modern and actively maintained libraries such as CGAL, GDAL, and Boost, ensuring efficient processing and accurate output data. The software uses a command-line interface (CLI) controlled via YAML configuration files for input and processing parameters, increasing its flexibility and extensibility.

In terms of performance, 3dfier is designed to efficiently handle large urban areas, as demonstrated by its use at the Dutch National Mapping Agency (Kadaster) for creating the 3D base registration information of the Netherlands. Additionally, due to its accurate output, it is particularly suitable as input data for environmental simulation software.

For this project, the 3dfier software will be utilized to process ALS and MLS data of the Technical University of Munich (TUM) and its surrounding area. The objective is to generate LoD1 model of this area using 3dfier, effectively distinguishing buildings and their surrounding terrain(buildings or roads). It is anticipated that 3dfier will efficiently utilize ALS data to construct the LoD1 model of the area, accurately distinguishing the point cloud data of buildings from the surrounding terrain. However, since MLS data typically captures only parts of building facades and cannot fully cover the building footprint or the entire building area, it is expected that using MLS data alone may not result in a complete LoD1 model. Nonetheless, when ALS and MLS data are combined, the point cloud data is likely to cover the entire area more comprehensively, potentially resulting in a more accurate building height model. Through this experiment, 3dfier is expected to accurately reconstruct the 3D urban model of this area, demonstrating its capability to handle large-scale geospatial data and integrate data from different scanning technologies, further proving its wide applicability in urban modeling and environmental analysis.

3.3 Polyfit:

PolyFit is a framework designed for converting point clouds into detailed, lightweight polygonal surface models. This approach sets itself apart by focusing on the intersection of planar primitives to form seamless, boundary-free polygonal surfaces, rather than merely extracting or arranging geometric primitives. By framing the reconstruction process as a binary labeling challenge, PolyFit generates and optimizes a set of face candidates through binary linear programming. This ensures the creation of manifold and watertight models. PolyFit excels in producing detailed models from various planar objects, effectively capturing sharp features and demonstrating resilience against noise, outliers, and incomplete data. This advanced capability positions PolyFit as a valuable tool for sophisticated 3D geometric reconstructions.

Polyfit reconstructs models composed of planar segments such as buildings and other man-made structures by treating the reconstruction process as a binary labeling problem. The working steps are as follows:

1. Primitive Plane Extraction: Polyfit first uses the RANSAC[20] algorithm to detect plane segments from the input point cloud, representing potential parts of the final 3D model. Intersection and Hypothesis: After identifying these plane primitives, the software intersects them to generate a large number of candidate planes. This hypothesis is based on the idea that real structures will be a subset of these intersecting planes.

2. Closed Planes Selection: From the numerous candidate planes, Polyfit selects the optimal subset that best represents the actual objects. This selection is done through an optimization process that aims to balance data support, compactness, and geometric accuracy of the model. The optimization is formulated as a binary linear programming problem, where constraints ensure the final model is manifold (accurately representing a three-dimensional shape without gaps or overlaps) and watertight (without holes in the model).

3. Sharp Feature Recovery: Polyfit excels at recovering sharp features and edges of buildings, which is crucial for maintaining the fidelity of the architecture. The framework is robust against noise, outliers, and missing data, enhancing its practical applicability in real-world scenarios where data imperfections are common.

For Level of Detail 2 (LoD2) models, which include basic shapes as well as roof structures and other building features:

Detailed Plane Segmentation: Polyfit refines its initial plane segments to more closely match the geometry of roof structures and intricate building details.

Advanced Optimization: The optimization phase is critical for ensuring these detailed features are accurately represented in the final model. It selectively combines hypothesized planes based on their alignment with actual data points and the overall geometric consistency of the model.

Polyfit performs exceptionally well in environments requiring high precision and detailed architectural features. It employs advanced computational techniques to ensure that the models are not only accurate but also suitable for simulations and visualizations. By treating surface reconstruction from point clouds as a binary labeling problem, Polyfit introduces a structured and efficient approach to 3D modeling, accommodating various levels of detail and complexities in building projects. The lightweight, accurate, and feature-rich polygonal models generated by this method make it a valuable tool for urban planning, virtual reality, and architectural preservation.

In terms of expected performance for ALS data, point clouds are typically denser for rooftops but sparser for building facades. Polyfit is therefore expected to effectively reconstruct corresponding building roofs and use simple planes to adequately fit building facades. This method should correctly display standard building models and accurately clip real building shapes using closed planes. However, for MLS data, due to the lack of extensive roof information and the difficulty in achieving a closed point cloud, Polyfit may struggle to find suitable plane closures to simulate building roofs, possibly leading to reconstruction failures. For combined ALS and MLS data, the more comprehensive coverage of building point cloud data is anticipated to result in better fitting outcomes than ALS alone, potentially achieving higher accuracy in LoD2 models.

3.4 Evaluation Criteria

After the 3D reconstruction by 3dfier and Polyfit, generated architectural models will be compared with the LoD2 ground truth from Geoportal Bayern or original point cloud to evaluate the quality of the final models. Two main methods of model evaluation will be employed: Cloud-to-Mesh (C2M) and Hausdorff-Distance(HD).

Cloud-to-Mesh Distance (C2M):
The Cloud-to-Mesh distance is a method that calculates the nearest distance from point cloud data to a three-dimensional mesh model, primarily used to evaluate the distance between a model and its corresponding point cloud data, thereby quantifying the model's precision and error[21]. The process begins by selecting each point in the point cloud as a starting point, then searching for the nearest surface point within the mesh model.Spatial indexing structures such as KD-Trees is often used to accelerate this search process. Subsequently, the direct distance from each point in the cloud to the nearest surface point on the mesh is calculated. All these distances are then subjected to statistical analysis, including the calculation of average distance, maximum distance, and standard deviation, to evaluate the overall quality and error distribution of the model. This method provides users with an intuitive way to understand the congruence of the 3D model with the original point cloud data, making it an invaluable tool in quality control, model verification, and research. It effectively aids in assessing and improving the quality of 3D reconstructions.

Hausdorff-distance(HD):
The Hausdorff distance is a robust measure used to determine the extent of similarity between two point sets, typically used in comparing geometric shapes[22]. For two finite sets of points, $A = \{a_1, \ldots, a_m\}$ and $B = \{b_1, \ldots, b_n\}$, the Hausdorff distance is calculated as:

The Hausdorff Distance $H(A, B)$ between two point sets A and B is defined as:

$$HD(A, B) = \max(h(A, B), h(B, A))$$

where

$$h(A, B) = \max_{a \in A} \min_{b \in B} \|a - b\|$$

Here, $h(A, B)$ computes the maximum of all the minimum distances from each point in set A to the closest point in B, ensuring that the Hausdorff distance measures the greatest of these distances.

By using Hausdorff distance in experiments, both the LoD2 ground truth and the test models are sampled with a fixed number of points. This approach enables a straightforward and objective measurement of the differences between two models. Hausdorff distance is especially valuable in fields that demand high precision in model evaluation, such as digital forensics, medical imaging, and computer-aided design.

4 Experiments

4.1 Dataset

In this project, two types of point cloud data were utilized: Airborne Laser Scanning (ALS) and Mobile Laser Scanning (MLS).

4.1.1 ALS:

The ALS data was sourced from the Geoportal Bayern[23] official platform, which provides officially certified geographic data ensuring the quality and reliability of the data. As open-source data, it is not only free and readily accessible but also continually updated and maintained by bavarian government, ensuring the timeliness and accuracy of the data.

The ALS point cloud downloaded from Geoportal is divided into 1km x 1km grid areas, with each area containing over 20 million points, averaging over 20 points per square meter. Although this level of point cloud density may not capture detailed architectural features such as windows and thresholds, its ability to accurately identify roofs makes it suitable for urban modeling and the creation of Level of Detail 2 (LoD2) models.

Since the Technical University of Munich (TUM) campus is located on the data boundary line, some buildings were consequently segmented. To solve this problem, the first step was to merge point cloud data from four areas to form a complete dataset. Next, the point cloud for the TUM campus area was extracted from this dataset to serve as the foundation for further processing steps. All of these operations were performed using CloudCompare software.

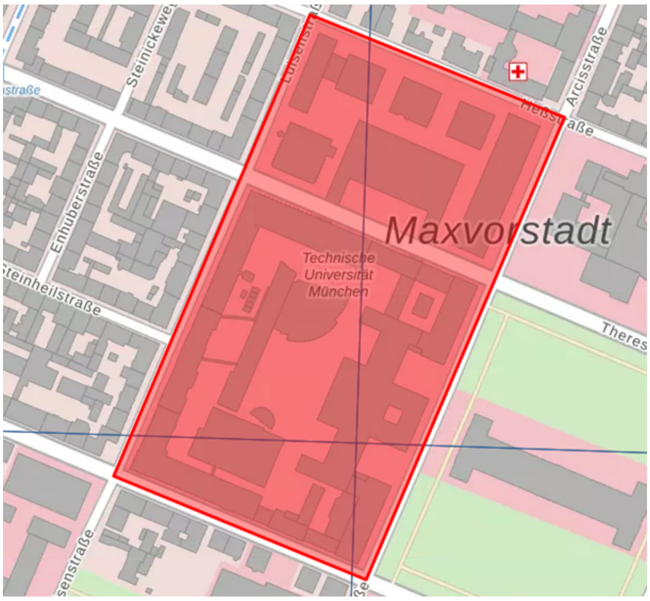

Figure 4.1 The TUM obtained from the Geoportal is divided into 4 areas

For 3dfier, the processed ALS data is adequate for use. However, when applying Polyfit to the vast TUM campus area, parameter adjustments often become challenging. Too many planes can overwhelm Polyfit's capacity to handle large datasets, while too few planes can result in insufficient architectural detail. To address this, specific test buildings must be isolated from the ALS data for Polyfit testing. Although Polyfit is robust against noise, outliers, and incomplete data, it still faces challenges when data is insufficient. Therefore, trees, cars, and other irrelevant elements should be clipped before use.

Figure 4.2 ALS point cloud of TUM area

4.1.2 MLS:

The MLS data was obtained from 3D Mapping Solutions GmbH using vehicle-mounted mobile laser scanning equipment[13], scanned along the roads surrounding TUM and captured the facades of relevant buildings. The same processing procedure applied to ALS data was also applicable to MLS data. Initially, specific building areas were trimmed from the TUM area's MLS point cloud. Due to the higher density and closer scanning distance of MLS, the wall facade data obtained is very precise. However, because the original MLS data volume is massive and often required extended loading times, downsampling (subsampling) was performed to optimize the efficiency of subsequent operations and ensure that ALS and MLS points received similar weighting during normal and plane generation. This operation was conducted in CloudCompare, reducing the data to 10

It is crucial to note that MLS data also contains significant environmental noise, such as trees, vehicles, and other non-architectural elements, which needed to be removed in CloudCompare. However, some noise caused by the "voyuer effect"[24]—data generated through windows or other transparent objects—was retained to explore how 3dfier and Polyfit handle this special type of noise and to evaluate their capabilities in processing such data.

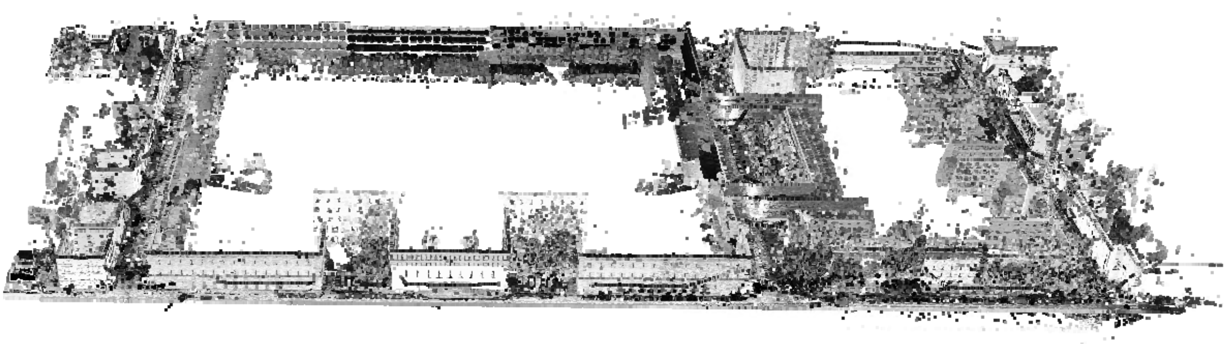

Figure 4.3 MLS point cloud of TUM area

4.1.3 ALS+MLS:

After processing the ALS and MLS data, preliminary georeferencing calibration using UTM32 (EPSG:25832) was performed in CloudCompare for the ALS and MLS data covering the TUM campus area, ensuring that both data types were accurately registered within a unified global coordinate system. To guarantee the accuracy of their relative positions, the combined ALS+MLS data was further subjected to high-precision registration in Leica Cyclone Register 360.

This step is critical as it ensures the spatial relative positioning and accurate alignment of the two point cloud data types, thus preventing the introduction of additional noise in the model reconstruction process due to data misalignment. Through precise geographic registration, the ALS and MLS data were effectively integrated, providing a clear and coherent foundation for subsequent 3D modeling. Moreover, this geographic referencing process not only involved aligning the point cloud data with the global coordinate system but also included a meticulous calibration step to ensure all point cloud data was precisely located both horizontally and vertically. This step enhances data quality and ensures seamless integration of point clouds from different sources.

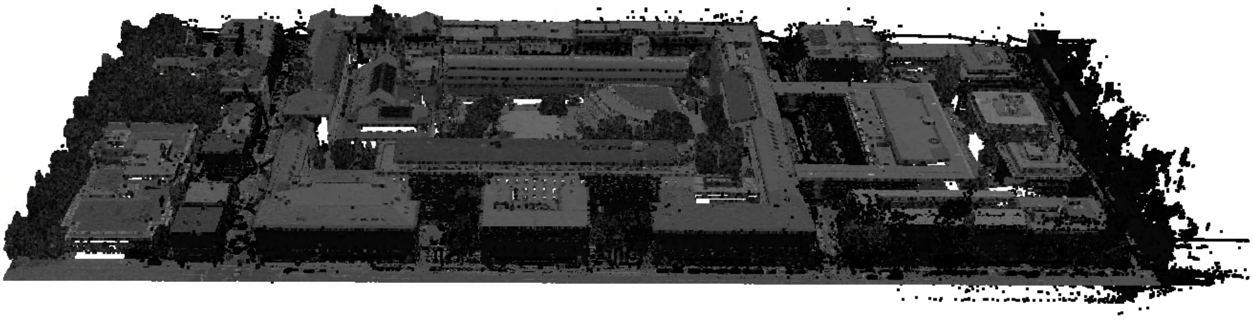

Figure 4.4 ALS+MLS merged point cloud of TUM area

4.2 Experimental setup

The overall experiment is primarily based on two software platforms, Polyfit and 3dfier. Both tools utilize the same data samples, but differ in the volume of data they process (3dfier calculates the point cloud for the entire campus area; Polyfit analyzes individual buildings) and the reconstruction levels of detail (3dfier targets LoD1, Polyfit targets LoD2).

4.2.1 3dfier:

During the point cloud reconstruction process with 3dfier, the building's footprint is serves as a crucial data source besides the point cloud data.

Footprint:
In urban modeling, a building's "Footprint" refers to the outline of the area directly occupied or covered by the building on the ground, as seen from a top view. This outline represents the portion of the building that makes contact with the ground. Footprint data is vital for planning urban layouts, calculating building density, and conducting land use analysis. It not only helps planners precisely understand the space occupied by each building but also serves as the basis for spatial analysis, environmental impact assessments, and 3D urban simulations.

In LoD1 point cloud reconstruction using 3dfier, the building's footprint is an essential metric. 3dfier requires it as ground truth to project the data from the point cloud onto it. Furthermore, different gml_ids within the footprint help 3dfier distinguish between buildings, allowing it to generate independent LoD1 models for each building.

Currently, there is no open-source method to directly obtain footprints for the TUM building complex, so this data must be generated anew. Additionally, data that can distinguish buildings and contains gml_ids is required. The LoD2 models provided by Geoportal Bayern are used as the source data, and FME is employed to extract the desired building area, select the relevant building complex and convert into a 2D Footprint.

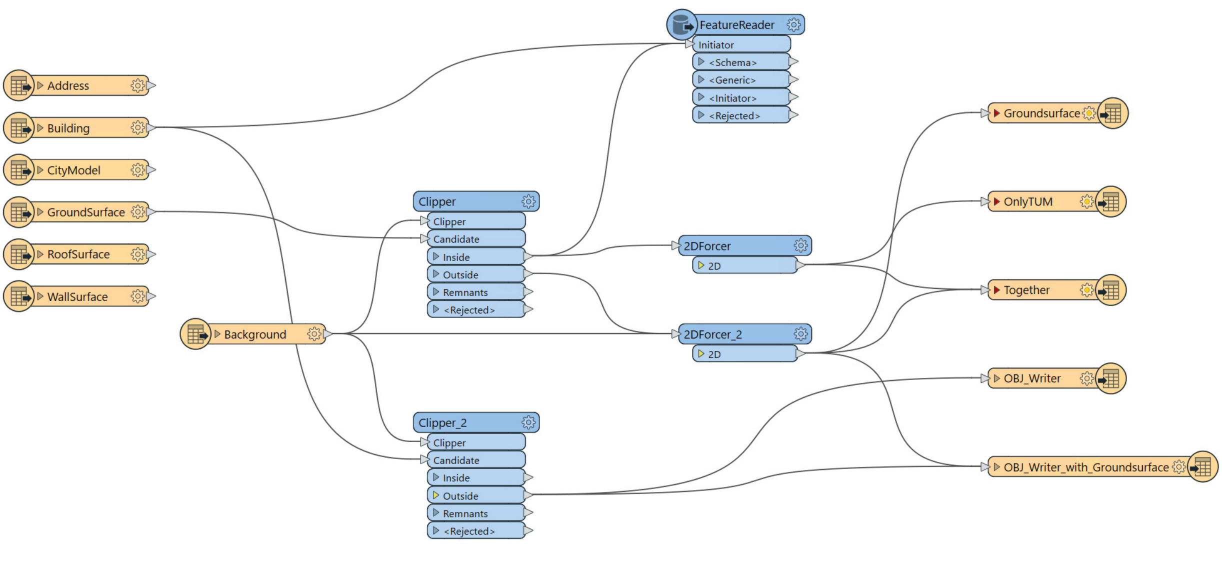

Figure 4.5 FME Workflow

However, since FME can only save in .shp format, and 3dfier requires data in .sqlite format, the exported .shp files need to be converted by using QGIS. Once the .sqlite file is successfully exported, the preparation of the footprint is considered complete.

After completing all preliminary preparations of the footprint, 3dfier still requires editing its .yaml configuration file. This necessary step involves setting specific attributes for the graphical styles within the footprint, enabling 3dfier to identify whether the depicted patterns represent buildings, roads, or river areas. For this purpose, 3dfier employs the universal LAS file classification standard, primarily distinguishing between road/ground (class 11/2) and buildings (class 9) within the experimental area. Particular data elements present in rooftop areas, such as smoke or wires, are generally categorized under undefined classes (0/1).

Classification value	Meaning
0	Created, Never classified
1	Unassigned
2	Ground
3	Low Vegetation
4	Medium Vegetation
5	High Vegetation
6	Building
7	Low Point
8	Model Key-Point
9	Water
10	Rail
11	Road Surface
12	Reserved
13	Wire - Guard (Shield)
14	Wire - Conductor (Phase)
15	Transmission Tower
16	Wire-Structure Connector (Insulator)
17	Bridge Deck
18	High Noise
19	Reserved
20	Ignored Ground
21	Snow
22	Temporal Exclusion
23–63	Reserved
64–255	User Definable

Table 4.1 General LAS classification list [25]

The .yaml file contains numerous adjustable parameters, such as 'building_radius_vertex_elevation', 'radius_vertex_elevation', and 'threshold_jump_edges', which relate to the reconstruction details of buildings. These parameters influence the differentiation of building heights, the connections between buildings and roads, and the level of detail in building features. Although 3dfier can adjust the final Level of Detail (LoD), it is limited to settings between LoD0 (footprint) and LoD1, and can not generate LoD2 models. Additionally, the .mtl file provided by 3dfier assigns colors to the final architectural models based on their type, which greatly benefit the observation of subsequent model.

The experiment involves processing ALS, MLS, and combined ALS+MLS point cloud data as three different data sources with the same Footprint, ensuring that each dataset is analyzed under consistent conditions.

4.2.2 Polyfit:

PolyFit employs direct plane fitting to point clouds without the need of the building's footprint, differing it from tools like 3dfier and City3D that use architectural footprints for reconstruction. Due to its computational approach of calculating planes from point clouds and exploring possible combinations to identify the optimal reconstruction method, Polyfit is not suitable for large-scale reconstructions like the entire TUM building complex. Instead, Polyfit excels in reconstructing individual buildings by combining appropriately extracted planes to form accurate models.

Consequently, Polyfit necessitates segmentation of buildings within the existing point cloud data. For this project, the buildings are categorized based on complexity in three levels (simple, moderate, challenging), each category selects three buildings to attempt point cloud reconstruction:

Simple: StudiTUM, Kunstareal, FernUNI
Characteristics: Smaller building volume; lower point cloud data volume; simple structure requiring few planes; comprehensive point cloud coverage; standalone buildings.

Moderate: N5, N8, Hochvolthaus
Characteristics: Point clouds generally cover structural facades; standalone buildings; moderate building volume; varied roof structures.

Challenging: 0503, 0507, Haupteingang
Characteristics: Buildings are interconnected, not standalone; large building volume and complex structures; point clouds do not fully cover all facades.

This structured approach allows Polyfit to effectively manage the complexity and specifics of each building type, optimizing the reconstruction process and ensuring reliable and detailed modeling outcomes.

Additionally, the extraction of planes from point clouds in PolyFit relies on the extraction of normal vectors from the cloud, which introduces two distinct parameter requirements: **Estimate Normals from different amount of Neighbor Points** and **Extract Primitives from different minimum support**, with **"Primitives"** referring to the planes being sought.

To study the impact of these parameters on experimental outcomes, a gradient series of tests was set up for each parameter: **Estimate Normals from different amount of Neighbor Points** with values of 30, 50, and 100; **Extract Primitives from different minimum support** with values of 30, 50, 100, 300, 500, and 800. In total, 162 experiments were conducted on 9 buildings, with the goal of identifying the parameter settings most suited for reconstructing models of varying building sizes.

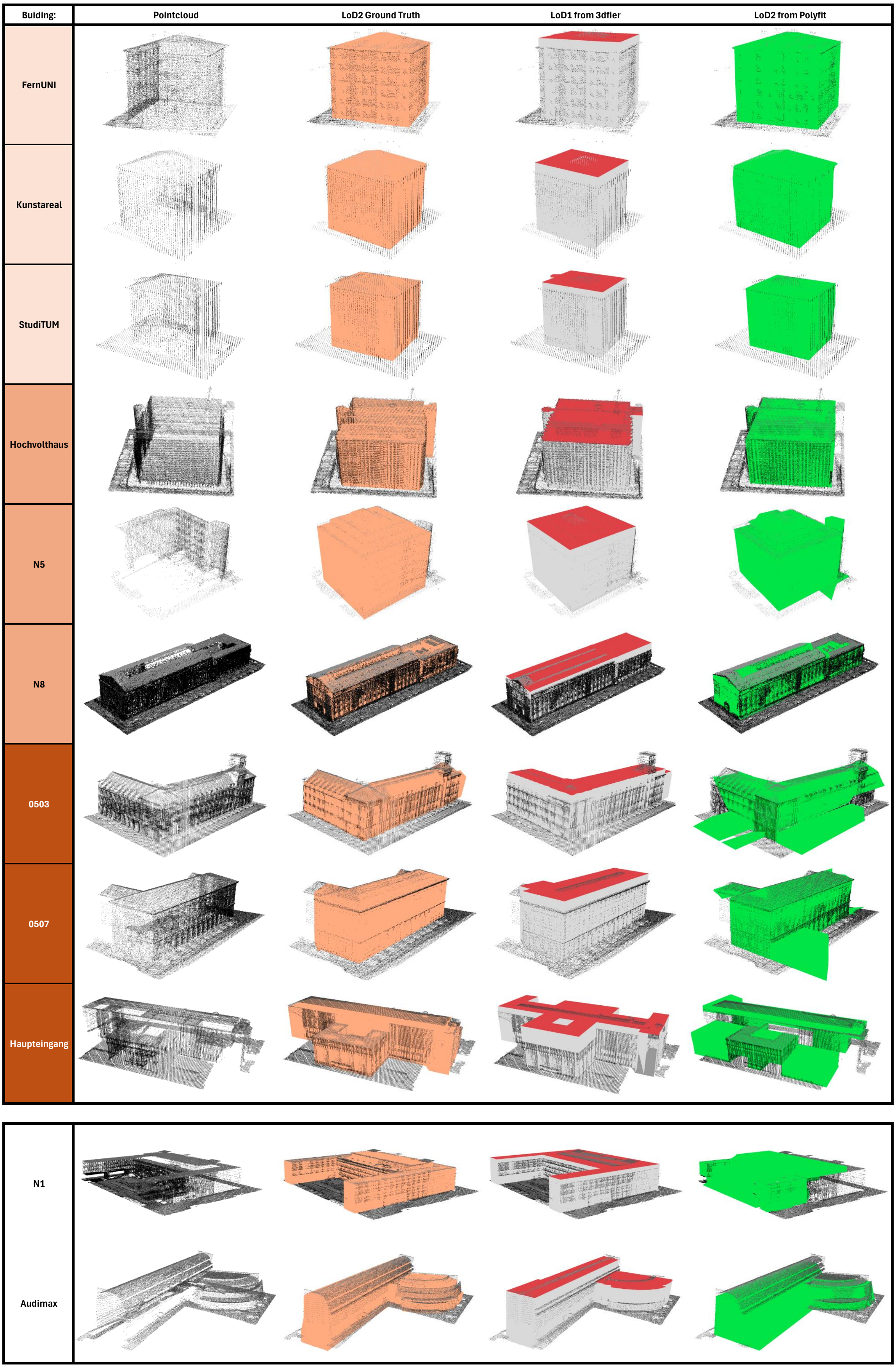

Figure 4.6 Overview of ALS+MLS point cloud, point cloud+LoD2(ground truth from Geoportal-Bayern), point cloud+LoD1(3dfier), point cloud+LoD2(Polyfit)

4.3 Results

4.3.1 3dfier:

In the reconstruction process 3dfier uses three different data sources (ALS+MLS, ALS, and MLS), it can be discovered that ALS and ALS+MLS successfully outputted the corresponding LoD1 models while the MLS data did not. This failure was primarily due to the MLS data not completely covering the building's Footprint but only the road areas.

Additionally, it was observed that if the point cloud only covers parts of buildings areas, 3dfier tends to generate highly unreasonable model areas, sometimes even producing negative height values. This issue can be resolved by ensuring that the point cloud fully covers all relevant areas.

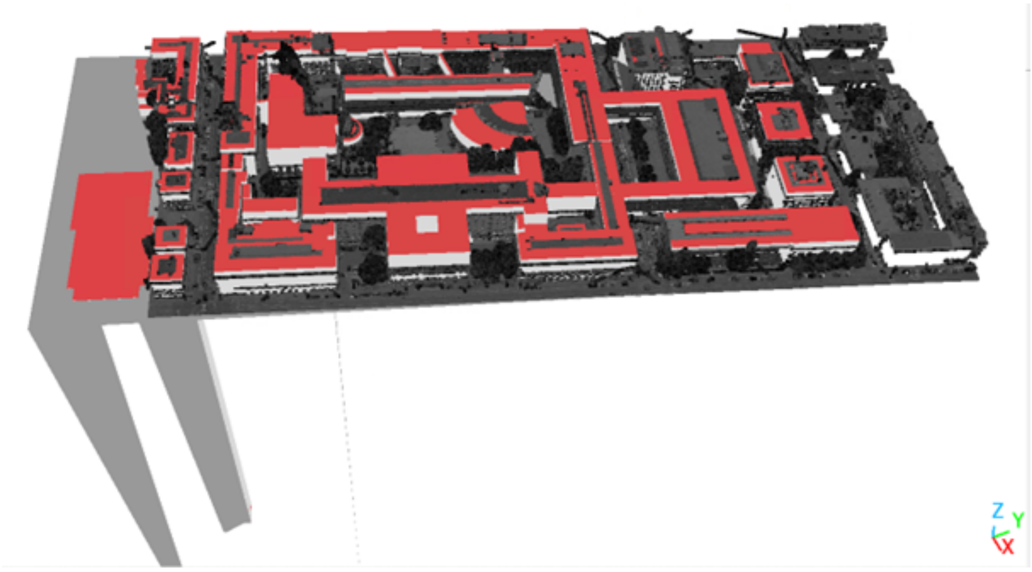

Figure 4.7 LoD1 from 3dfier with ALS point cloud (ALS can not cover the footprint area)

During the processing of ALS and ALS+MLS data, an issue was identified at the junction of buildings 0501 and 0502 at TUM: the generated connection point was significantly lower than the normal level. To solve this, trimming was carried out in CloudCompare, retaining only the normal areas of the buildings.

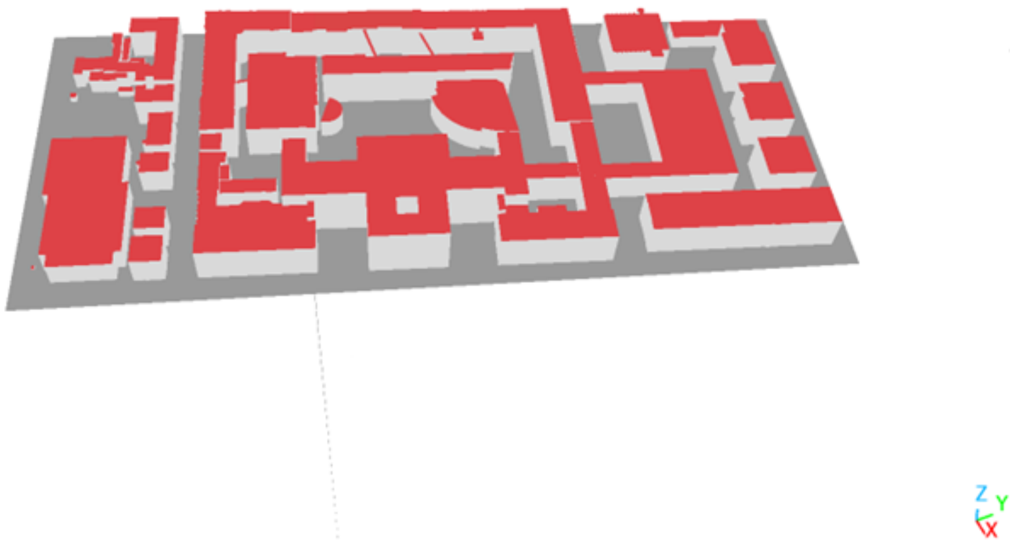

Figure 4.8 LoD1 from 3dfier with ALS point cloud (ALS can cover the footprint area)

Subsequently, the trimmed models were placed in MeshLab[26], and discrepancies between them were calculated using the Hausdorff distance with 10,000,000 sampling points.

The results showed a minimum distance of 0.000m, a maximum of 1.500m, an average of 0.056m, and an RMS of 0.149m. However, the model-vertex-quality is a constant and when setting ALS+MLS model as the reference mesh, the Distance from Reference Mesh computed showed a maximum error of 0.000m, a mean error of 0.000m, and an RMS of 0.000m.

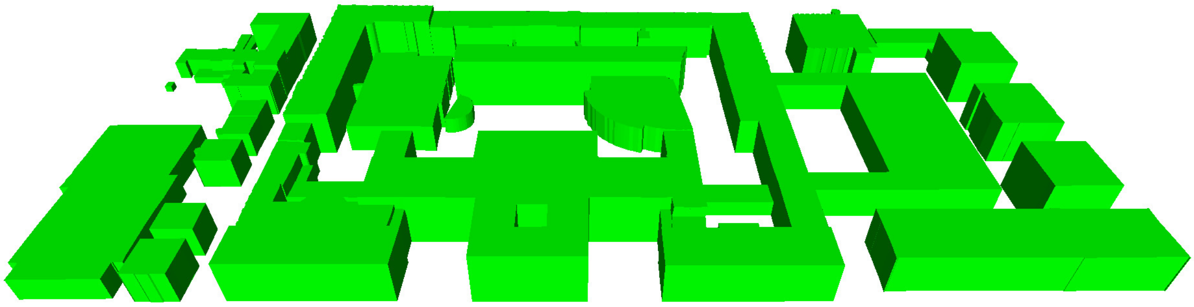

Figure 4.9 LoD1 model textured with Referenced Mesh Distance, ALS+MLS based model as referenced mesh (distance constant=0)

Such error values are kept below the centimeter scale, which can be completely ignored within the scale of a campus.In this case, those 2 models can be assumed as the same.

Currently, there is no open-source product available for the LoD1 model generated by 3dfier. Although the Bundesamt für Kartographie und Geodäsie (BKG) possesses an LoD1 model for all of Germany, the licensing restrictions limit this dataset's use to federal agencies and projects receiving at least 50% of their funding from the federal government. Thus, there is no suitable reference standard for quality assessment of LoD1 model data. Therefore, the quality assessment of the LoD1 model can only be conducted by comparing it with the original point cloud data, specifically by calculating the Cloud to Mesh (C2M) distance.

Since the models generated by ALS and ALS+MLS are consistent, the model generated by ALS+MLS is used for C2M calculations with the original ALS, MLS, and ALS+MLS point cloud data and compare the results with the C2M of official LoD2 model.

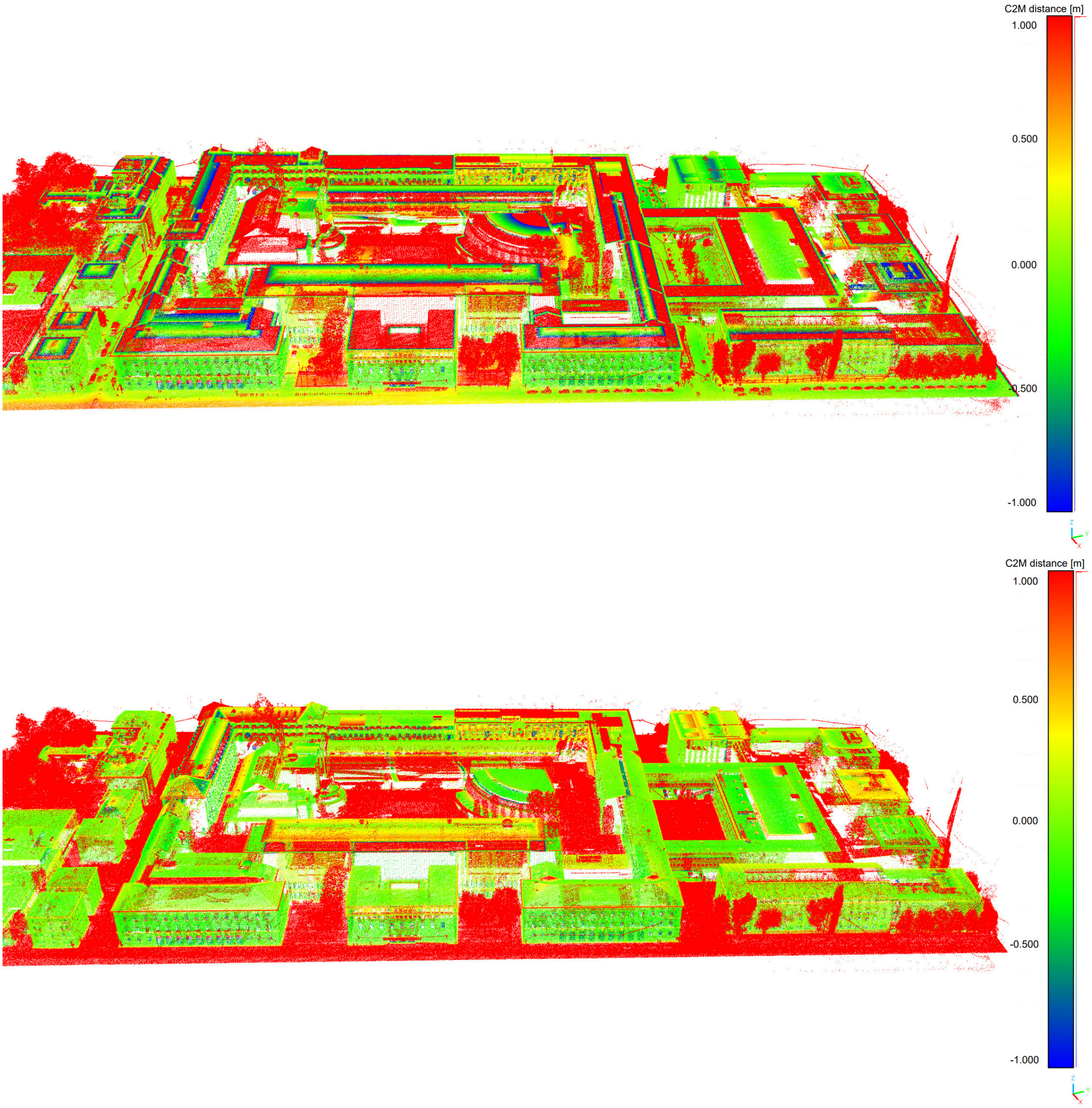

Figure 4.10 fig:Comperasion between C2M results of LoD1 model from 3dfier and LoD2 ground truth (Up: C2M results of LoD1 | Down: C2M results of LoD2)

When setting 10,000,000 sampling points to calculate the Hausdorff Distance to measure the discrepancies between the two models, the maximum error was 15.580m, the mean was 0.834m, and the RMS was 1.746m. Although some data points showed significant errors, the overall errors were kept within 2 meters. Notably, the errors were primarily concentrated around the roof areas, while the middle parts of the building roofs typically exhibited smaller discrepancies. This is consistent with the difference between LoD1 and LoD2 models, where the LoD1 model tends to abstract the middle part of the roof triangle into a single plane.

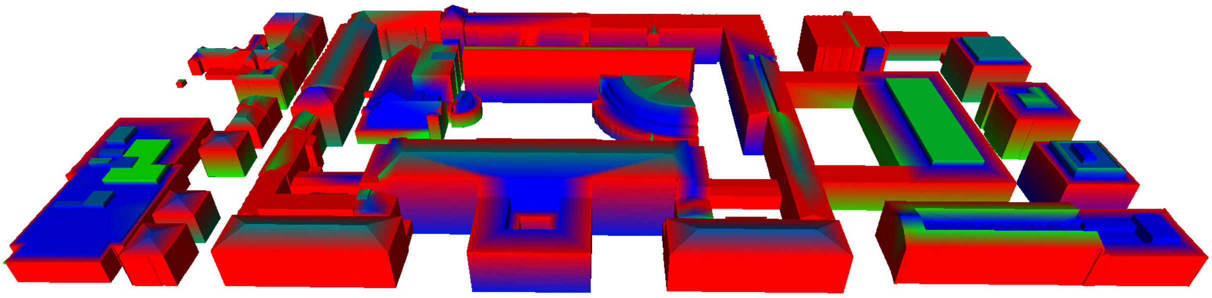

Figure 4.11 LoD2-Groundtruth textured by Hausdorff-Distance with LoD1 model (Red:close(0m) | Green:distance between 0m and RMS | Blue:distance with RMS-worth[1.75m])

When setting the LoD1 model as the reference mesh to calculate the distance in between, it is obtained the results of Reference-Mesh-Distance with a maximum of 15.580m, a mean of 1.390m, and an RMS of 2.610m. According to the colored model, the discrepancies primarily occur in areas with complex and highly variable roof structures, such as the N8 rooftop or the Audimax. The overall fluctuations are not significant, indicating that the model's precision meets the practical application requirements.

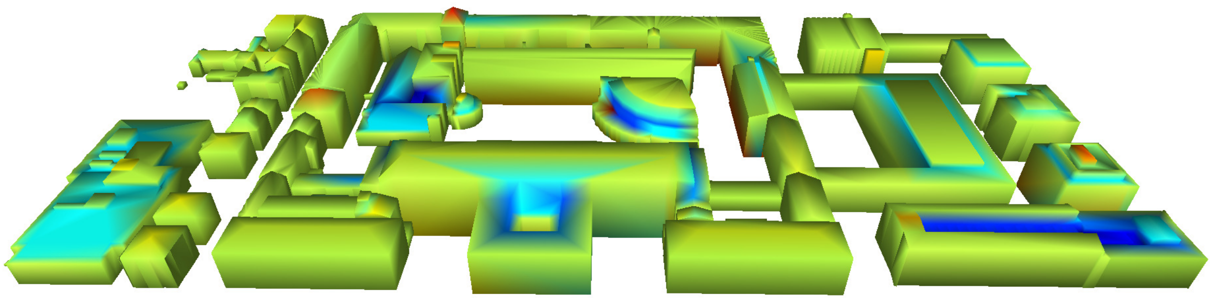

Figure 4.12 LoD2-Groundtruth textured by Reference-Mesh-Distance with LoD1 from 3dfier, LoD1 as Reference Mesh (Red:Negative Distance[max:-0.3m] | Green:Zero[distance between -0.3m~0.3m] | Blue:Positive Distance[max:+0.3m])

Using CloudCompare, the nine buildings designated for reconstruction by Polyfit are extracted and compared with the LoD2 ground truth data from Geoportal Bayern.

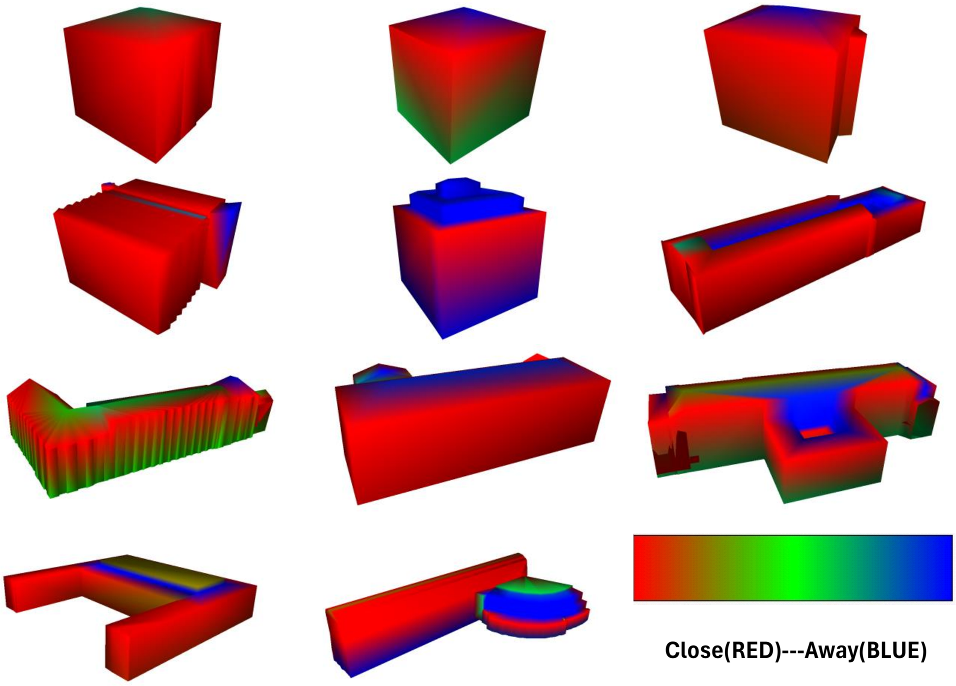

Figure 4.13 LoD2 buildings textured by Hausdorff-Distance with LoD1 from 3dfier(Red:close(0m) | Green:distance between 0m~1m | Blue:1m)

The Hausdorff distance between the reconstructed LoD1 models and the LoD2 ground truth are also calculated to compare with the accuracy of the Polyfit reconstructions.

Buiding:	**Hausdorff Distance**		
	max	mean	RMS
FernUNI	1.532	0.222	0.390
Kunstareal	1.601	0.271	0.425
StudiTUM	1.532	0.179	0.316
Hochvolthaus	1.470	0.179	0.291
N5	4.020	0.947	1.425
N8	9.399	1.754	3.319
0503	4.952	0.510	0.948
0507	3.350	0.324	0.665
Haupteingang	15.580	1.364	2.569
N1	3.690	0.610	1.235
Audimax	8.109	0.840	1.403

Table 4.2 Hausdorff-Distance results of LoD1 buildings from 3dfier (LoD2 from Geoportal Bayern as ground truth)

4.3.2 Polyfit:

PolyFit's experiments are primarily focused on the analysis of specific buildings, utilizing three categories of buildings and three types of point cloud data. For assessing the reconstruction quality, Hausdorff Distance calculations are performed by MeshLab.

Simple: StudiTUM, Kunstareal, FernUNI

Moderate: N5, N8, Hochvolthaus

Challenging: 0503, 0507, Haupteingang

It first needs to use Mapple to estimate normals and primitives(planes) so that it can be put into Polyfit to rebuild the LoD2 model. In this project, 18 operations were performed on each building according to the parameter gradient. Not all of the experiment are scusseded, Polyfit can not generate all the models with the given parameters.

Estimate Normals from different amount of Neighbor Points: 30, 50, 100

Extract Primitives from different minimum support: 30, 50, 100, 300, 500, 800

ALS+MLS							
FernUNI (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	✓	✓	✓	✓	✓
	50	✓	✓	✓	✓	✓	✓
	100	✓	✓	✓	✓	✓	✓
Kunstareal (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	✓	✓	×	×	×
	50	✓	✓	✓	×	×	×
	100	✓	✓	×	×	×	×
StudiTUM (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	✓	×	×	×	×
	50	✓	✓	×	×	×	×
	100	✓	✓	×	×	×	×
Hochvolthaus (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	✓	✓	✓	×
	50	×	×	✓	✓	✓	✓
	100	×	×	✓	✓	✓	×
N5 (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	✓	✓	×	×	×
	50	×	✓	×	×	×	×
	100	×	✓	✓	×	×	×
N8 (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	✓	✓	✓
	50	×	×	×	✓	✓	✓
	100	×	×	×	✓	✓	✓
0503 (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	✓	✓	✓
	50	×	×	×	✓	✓	✓
	100	×	×	×	✓	✓	✓
0507 (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	✓	✓	×
	50	×	×	✓	✓	✓	×
	100	×	×	✓	✓	✓	×
Haupteingang (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	✓	✓	✓
	50	×	×	×	✓	✓	×
	100	×	×	×	✓	✓	×
N1 (ALS+MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	✓	✓	×
	50	×	×	×	✓	✓	×
	100	×	×	×	✓	✓	×

Table 4.3 LoD2 reconstructions based on ALS+MLS-point cloud(✓:succeed | $\times$: $failed)$

ALS

FernUNI (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	×	×	×	×	×
	50	×	×	×	×	×	×
	100	✓	×	×	×	×	×
Kunstareal (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	×	×	×	×	×
	50	✓	×	×	×	×	×
	100	✓	×	×	×	×	×
StudiTUM (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	✓	×	×	×	×
	50	✓	✓	×	×	×	×
	100	✓	✓	×	×	×	×
Hochvolthaus (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	×	×	×
	50	✓	×	×	×	×	×
	100	✓	✓	×	×	×	×
N5 (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	×	×	×
	50	×	×	×	×	×	×
	100	×	×	×	×	×	×
N8 (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	✓	×	×	×
	50	×	×	✓	×	×	×
	100	×	×	✓	×	×	×
0503 (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	✓	✓	✓	×
	50	×	×	✓	✓	✓	✓
	100	×	✓	×	✓	✓	×
0507 (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	✓	✓	×	×	×
	50	✓	✓	✓	×	×	×
	100	×	×	✓	×	×	×
Haupteingang (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	✓	✓	✓	×
	50	×	×	×	✓	✓	×
	100	×	×	×	✓	✓	×
N1 (ALS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	×	×	×
	50	×	×	×	×	×	×
	100	×	✓	✓	×	×	×

Table 4.4 LoD2 reconstructions based on ALS-point cloud (✓:succeed | $\times$: $failed$)

MLS							
FernUNI (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	✓	×	×	×	×
	50	✓	✓	✓	×	×	×
	100	✓	✓	✓	×	×	×
Kunstareal (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	✓	×	×	×	×
	50	✓	✓	×	×	×	×
	100	×	×	×	×	×	×
StudiTUM (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	✓	×	×	×	×	×
	50	✓	×	×	×	×	×
	100	✓	×	×	×	×	×
Hochvolthaus (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	×	×	×
	50	×	×	×	×	×	×
	100	×	×	×	×	×	×
N5 (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	✓	×	×	×
	50	×	×	✓	×	×	×
	100	×	×	×	×	×	×
N8 (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	✓	✓	✓	✓
	50	×	×	×	✓	✓	✓
	100	×	×	×	✓	✓	✓
0503 (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	✓	×	×	×
	50	×	×	×	×	×	×
	100	×	✓	×	×	×	×
0507 (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	✓	✓	×
	50	×	×	×	✓	×	×
	100	×	×	×	✓	×	×
Haupteingang (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	×	×	×	×
	50	×	×	×	×	×	×
	100	×	×	×	×	×	×
N1 (MLS)		Extract Primitives from different minimum support					
		30	50	100	300	500	800
Estimate Normals	30	×	×	✓	✓	✓	✓
	50	×	×	✓	✓	✓	✓
	100	×	×	✓	✓	✓	✓

Table 4.5 LoD2 reconstructions based on MLS-point cloud(✓:succeed | $\times$: $failed$)

After successfully generating the LoD2 model of a single building, the model is first georeferenced using CloudCompare to align it with the geographic coordinate system of the LoD2 ground truth. Subsequently, the aligned LoD2 model and the ground truth are compared in MeshLab, where 1,000,000 sampling points per model are used to calculate the Hausdorff Distance. This metric is employed to assess the quality of the generated model.

The use of different datasets has a significant impact on the final reconstruction results. Taking the FernUNI building as an example, when ALS and MLS data are combined, PolyFit can generate all 18 models for FernUNI, indicating that regardless of how parameters are adjusted, Polyfit can consistently produce appropriate models for this building.

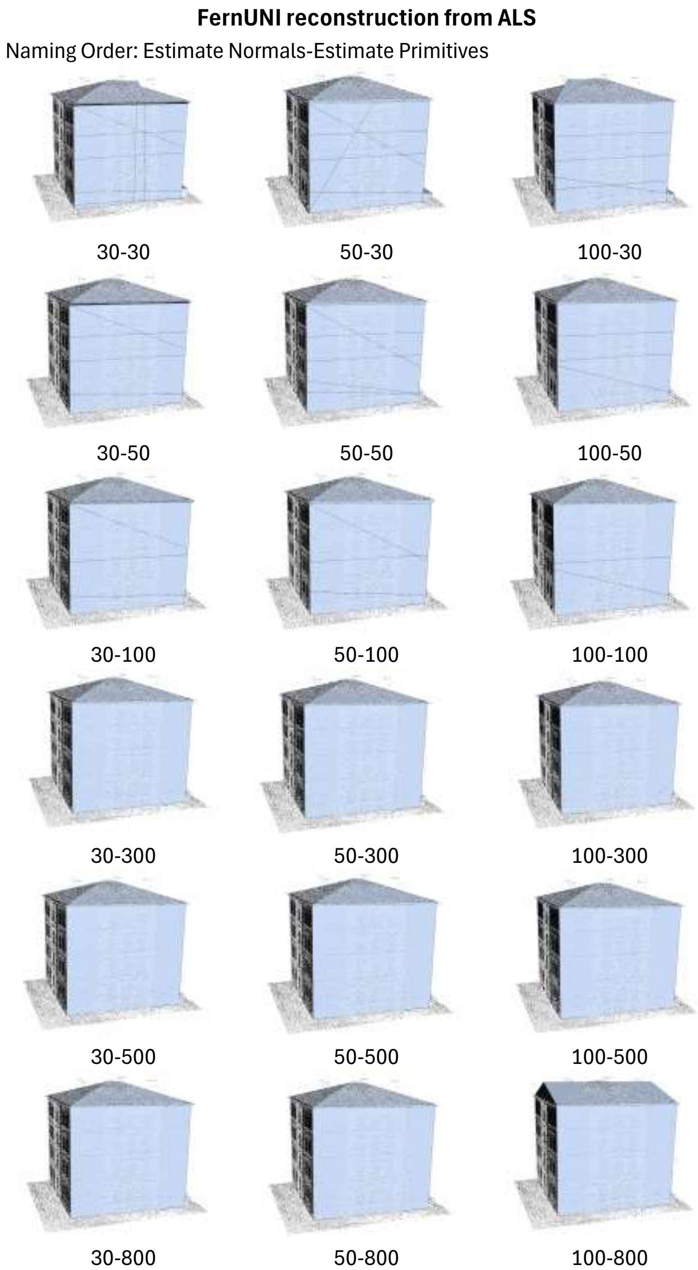

Figure 4.14 18 LoD2 StudiTUM-models reconstructed by Polyfit

In contrast, when only ALS data is utilized, due to its lack of wall facade data, only two accurate models can be produced, with other attempts incorrectly generating structures only in the rooftop area. This highlights the importance of comprehensive data coverage for achieving detailed and accurate architectural reconstructions.

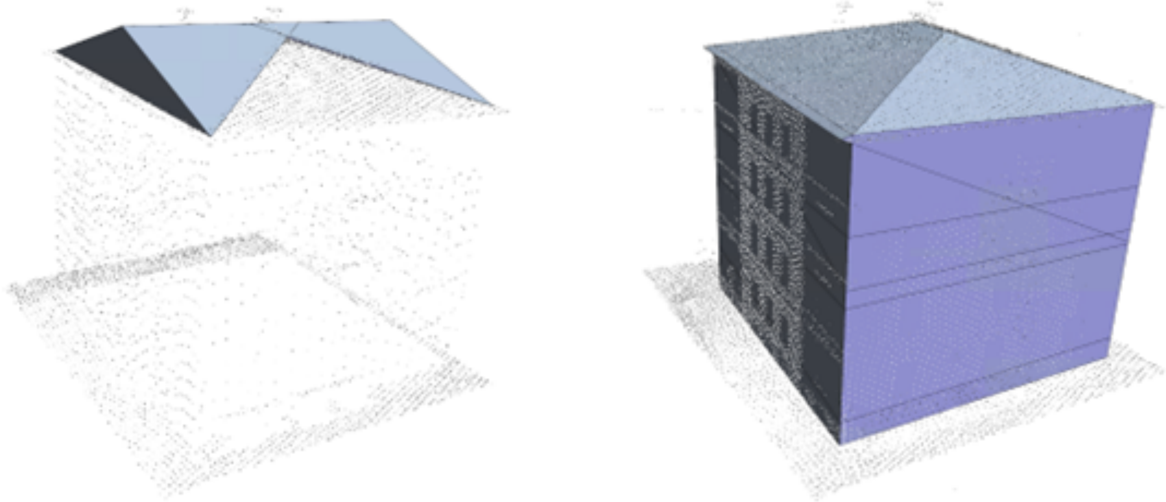

Figure 4.15 Comparison of LoD2 results of FernUNI from ALS-point cloud and ALS+MLS-point cloud with same parameters (Left:ALS | Right:ALS+MLS)

However, for buildings with complex facades, such as Hochvolthaus, ALS data only contains less information about its serrated facades than MLS. Therfor, ALS does not encounter overly complex scenarios during plane fitting calculations. Therefore, ALS can more accurately fit into a three-dimensional shape. On the contrary, MLS data is heavily affected by the complexity of the facades. The intricate details captured by MLS make it challenging for Polyfit to fit planes accurately, thus adversely affecting the model quality where facade complexity is high.

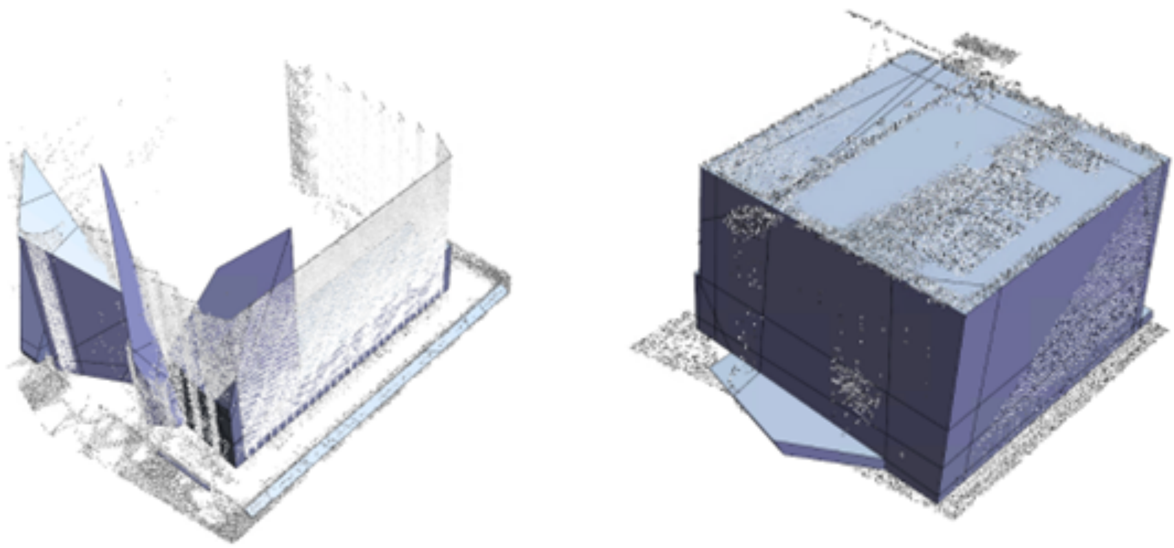

Figure 4.16 Comparison of LoD2 results of Hochvolthaus from MLS-point cloud and ALS-point cloud with same parameters (Left:MLS | Right:ALS)

On the other hand, when dealing with buildings have complex roof structures like the N8-building, MLS data's lack of scanning in that direction paradoxically results in a more complete overall structure, while ALS data tends to only produce the roof structures.

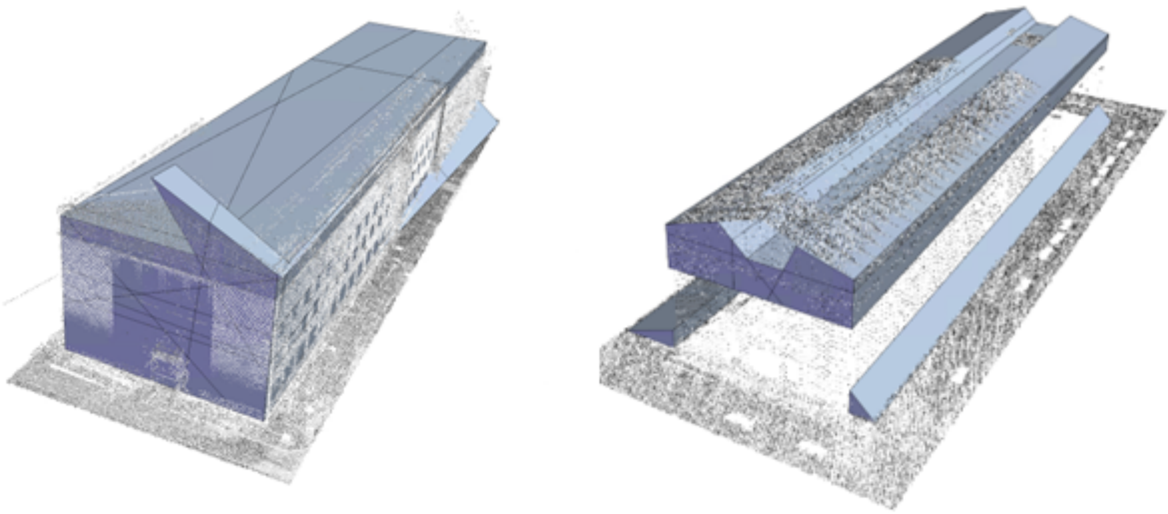

Figure 4.17 Comparison of LoD2 results of N8 from MLS-point cloud and ALS-point cloud with same parameters (Left:MLS | Right:ALS)

Besides, due to ALS's focus on rooftop features rather than structural facades, when confronted with complex structures like buildings 0503, 0507, and Haupteingang—where the point cloud data do not cover all areas—ALS still has the potential to reconstruct parts of the structures, but it is almost impossible for MLS.

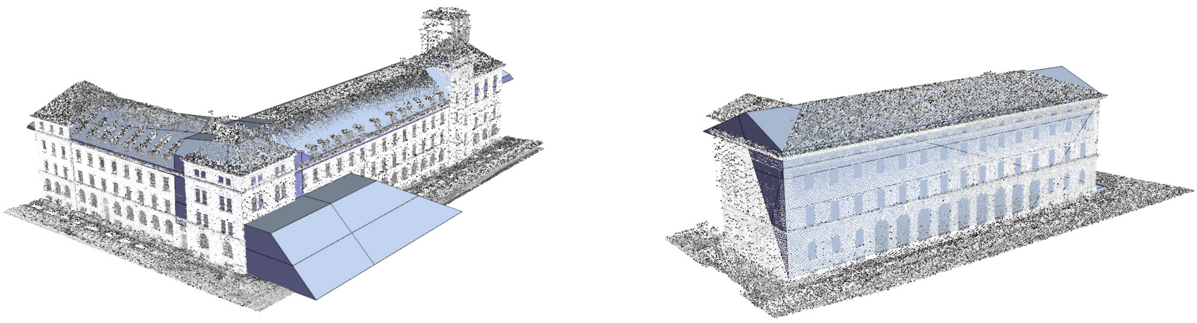

Figure 4.18 LoD2 of 0503 and 0507 buildings with point cloud(Left:0503 | Right:0507)

Buildings 0503 and 0507 are located at road corners, allowing MLS data to capture scans from two directions, which can sometimes result in the generation of similar structural features.

In addition to the 9 buildings of 3 different levels, an attempt was made to model building N1, which features two aerial walkways crossing Theresienstraße and are connected with other building. Both ALS and MLS scans struggle to fully capture the entirety of this building. The LoD2 ground truth also overlooks this detail, opting instead to create a solid model connected to the ground. As a result, reconstruction of N1 proved to be disastrous for Polyfit. No matter how the parameters were adjusted, the final models failed to meet requirements, only managing to generate the building's exterior and the plaza area enclosed by the building. Although its Hausdorff Distance results might not be particularly strange, in reality, it never successfully produced any models.

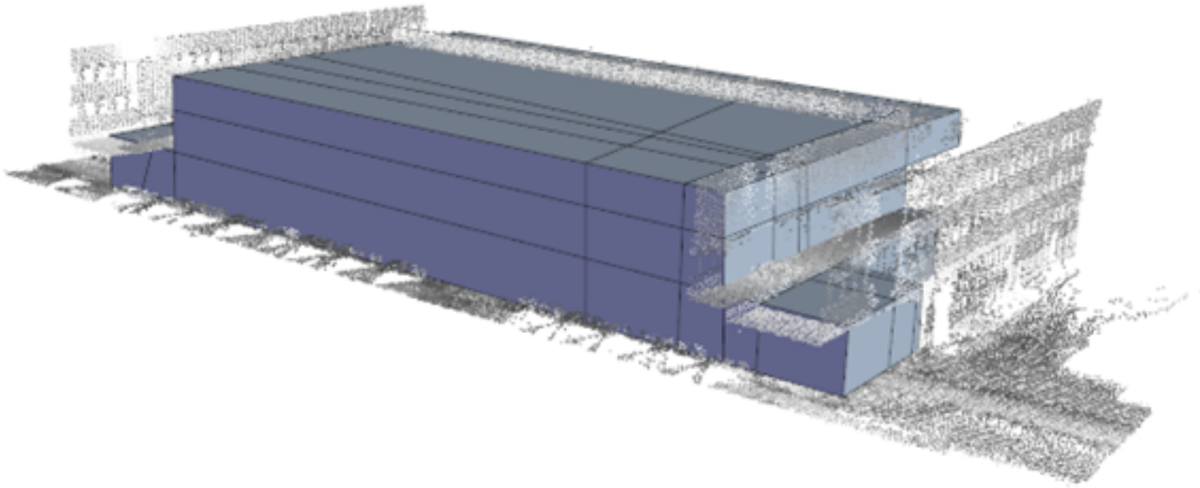

Figure 4.19 Comparison of MLS point cloud and the reconstruction results from Polyfit (N1-Building)

By using the C2M(cloud to mesh) calculation method to directly calculate the distance between the point cloud and the model, following results can be observed

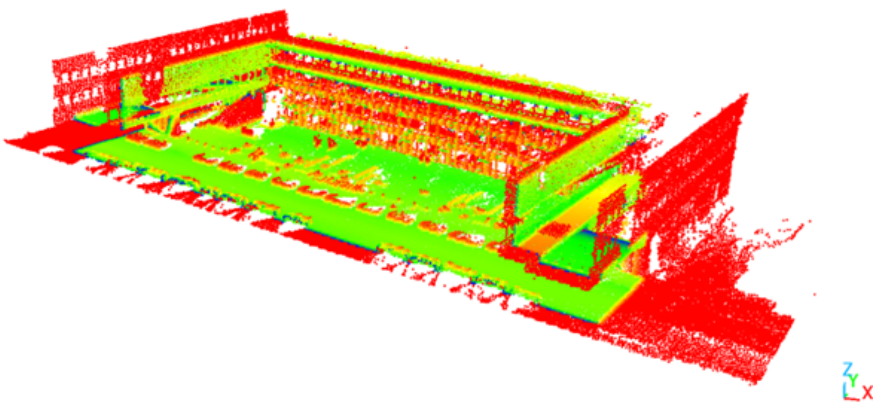

Figure 4.20 N1-C2M showing points in tolerance values (green) and out of tolerance (red) [Tolerance: 1m]

In the reconstruction of N1's LoD2 model, although the orientation of the model is completely incorrect, the C2M fit to the point cloud data is relatively accurate, with 53.5% (72,813/136,123 points) of the points within a 0.5m error margin, and most within 0.3m. This demonstrates that the point cloud data of the N1 building could be effectively abstracted into various planes by Polyfit, although its algorithm for finding closed surfaces could only identify the simplest combinations due to the complexity of N1.

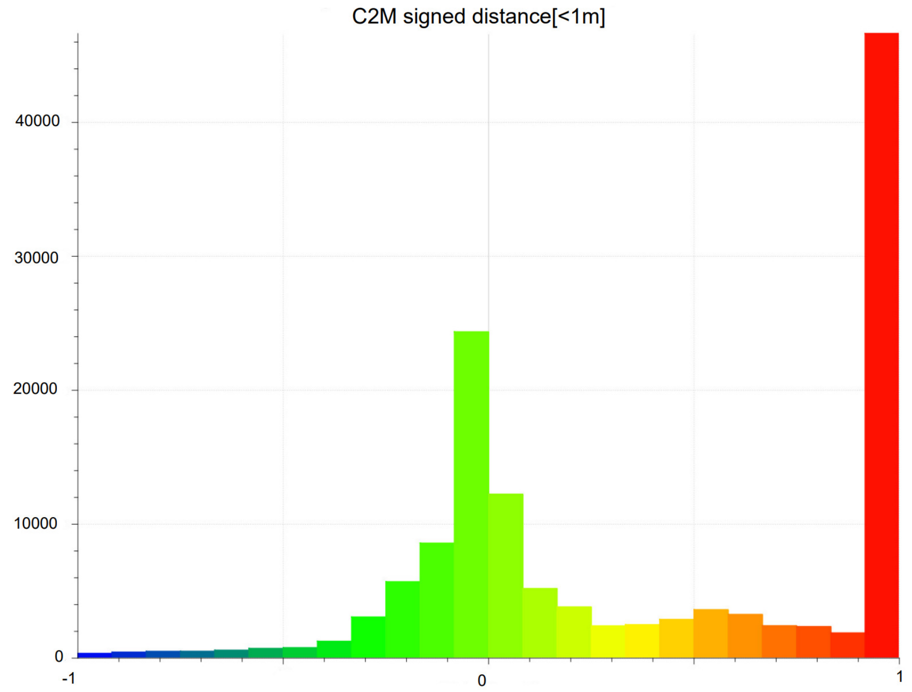

Figure 4.21 Cloud to Mesh Distance Histogram between ALS+MLS point cloud and reconstructed N1 building([X: distance -1m~1m; Y:count)

In addition to the N1 model, an attempt was also made to reconstruct the Audimax, the only building in the TUM complex with a curved roof. The unique architectural style and moderate scale of Audimax made it an ideal case study. The effects encountered when fitting architectural models to planes in the presence of curved structures were of particular interest. However, since the Audimax is located inside the TUM campus, the modeling experiment had to rely solely on ALS data.

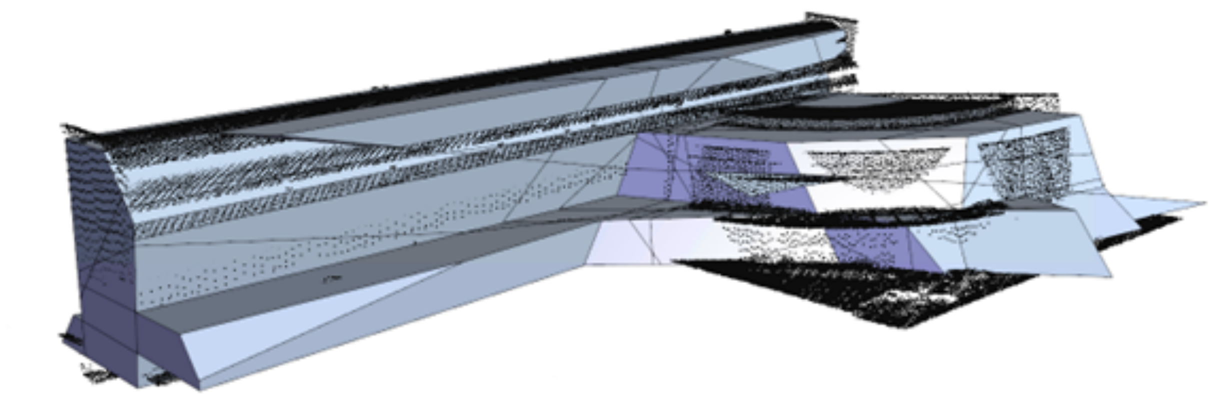

Figure 4.22 Audimax

Visually compared to the ALS point cloud data, Polyfit is able to essentially recreate the general style of Audimax, including its basic geometric features and the topological relationships between building components. Although Polyfit used relatively coarse large blocks of planes for segmenting and combining the point cloud, these combinations are sufficient to roughly identify the model as representing Audimax.

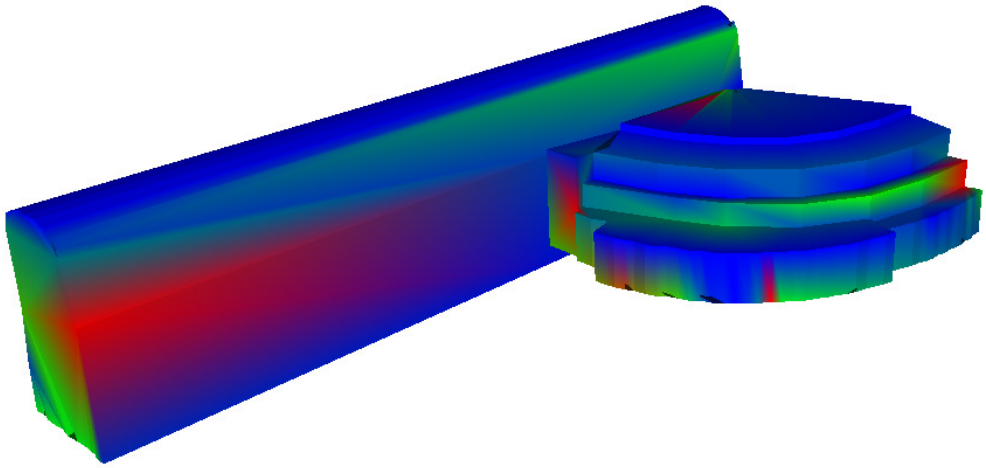

Figure 4.23 LoD2-Groundtruth textured by Hausdorff-Distance with LoD1 models (Red:close(0m) | Green:distance between 0m~RMS | Blue:RMS[2m])

Comparing with the LoD2 model, it's observable that the performance on the relatively vertical facades is quite satisfactory. However, the representation tends to be more mediocre on curved rooftops and multi-level sections. Overall, the model has managed to substantially recreate the intended architectural form.

This indicates that while Polyfit can efficiently handle straightforward or flat surfaces, its ability to accurately render more complex geometrical features like curves and detailed multilayer intersections still requires further refinement. Despite these limitations, the tool provides a fundamentally sound approximation of the building, which is commendable given the complexity involved in processing and rendering architectural nuances from point cloud data.

5 Discussion

5.1 3dfier:

According to the experimental results from 3dfier, MLS data does not serve as a reliable source for contributing to the construction of LoD1 models. The quality of the LoD1 model obtained by combining MLS with ALS data is consistent with the results obtained using ALS data alone. Therefore, it can be concluded that MLS does not play a significant role in algorithms like 3dfier that generate building LoD1 models based on architectural footprints. These algorithms rely directly on the building footprint, with the point cloud primarily providing relative rooftop height data and coverage of the building. The absence of complete coverage of the building's side facades has minimal impact on these types of algorithms. Thus, when only LoD1-level urban modeling is required, it is sufficient to only use ALS data.

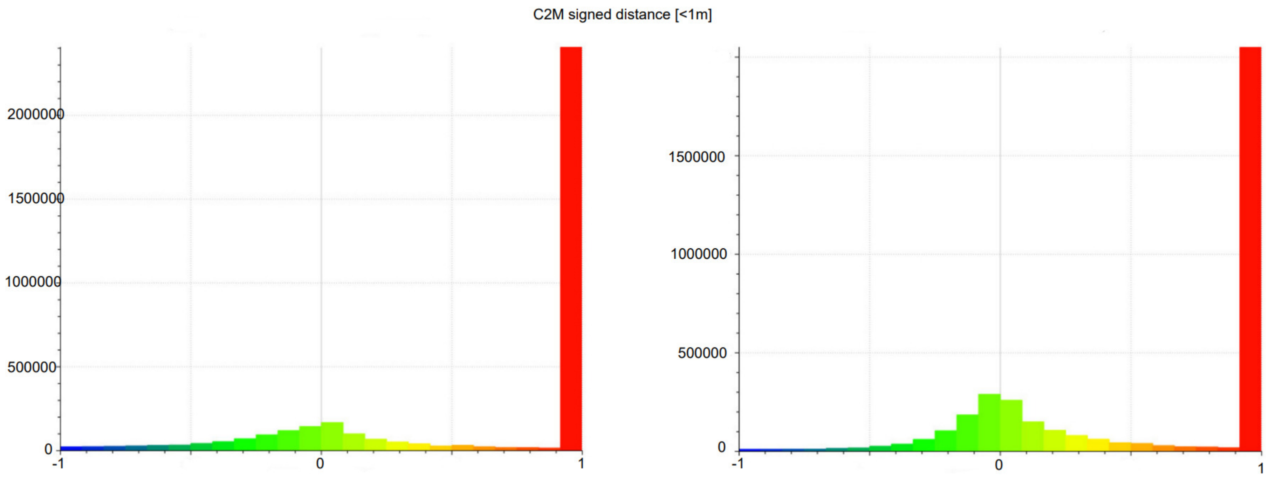

Figure 5.1 Cloud to Mesh Distance Histogram between ALS+MLS point cloud and reconstructed TUM campus (Left:LoD1(from 3dfier),Right:LoD2 groundtruth [X: distance -1m~1m; Y:count])

Based on C2M(cloud to mesh) statistical data of whole TUM camppus, the LoD2 model has 38.7% of points(1,420,057/3,668,950 points) with errors within 0.5 meters, while the LoD1 model has 27.2% (997,019/3,668,950 points) within this range.

This discrepancy is not primarily evident in the MLS data, where the LoD2 model has 36.8% of points (619,907/1,686,770 points) within 0.5 meters, and the LoD1 model has 37.3% (629,832/1,686,770 points). This indicates that both models have a similar fitting accuracy for building facades, with the LoD1 model even showing a 0.5% improvement in precision.

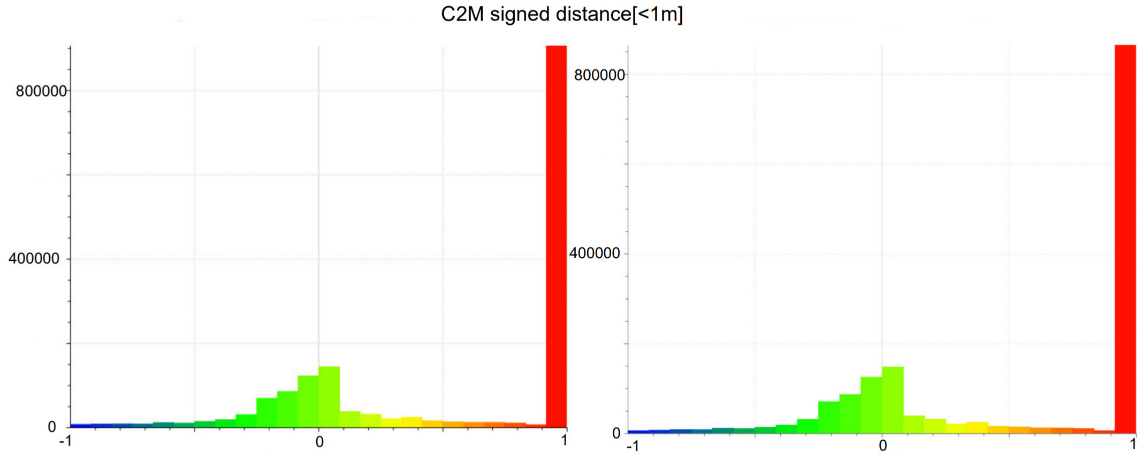

Figure 5.2 Cloud to Mesh Distance Histogram between MLS point cloud and reconstructed TUM campus (Left:LoD1(from 3dfier),Right:LoD2 groundtruth [X: distance -1m~1m; Y:count])

However, the difference between the two models is more pronounced in the ALS data, especially concerning roof details. The LoD2 model covers 38.2% (800,147/2,093,404 points) of this aspect, while the LoD1 model only covers 17.5% (367,181/2,093,404 points).

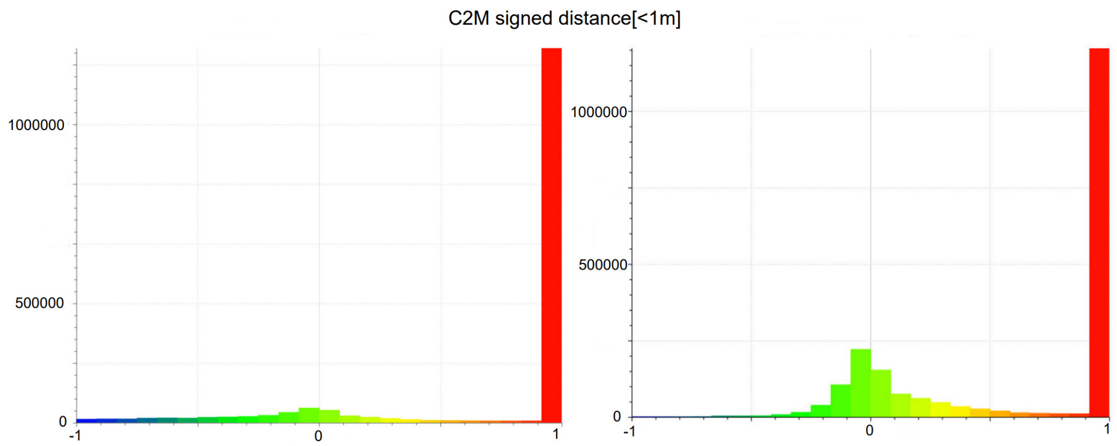

Figure 5.3 Cloud to Mesh Distance Histogram between ALS point cloud and reconstructed TUM campus (Left:LoD1(from 3dfier),Right:LoD2 groundtruth [X: distance -1m~1m; Y:count])

This result aligns with expectations, as a significant distinction between LoD2 and LoD1 models is the former's ability to differentiate roof details more finely.

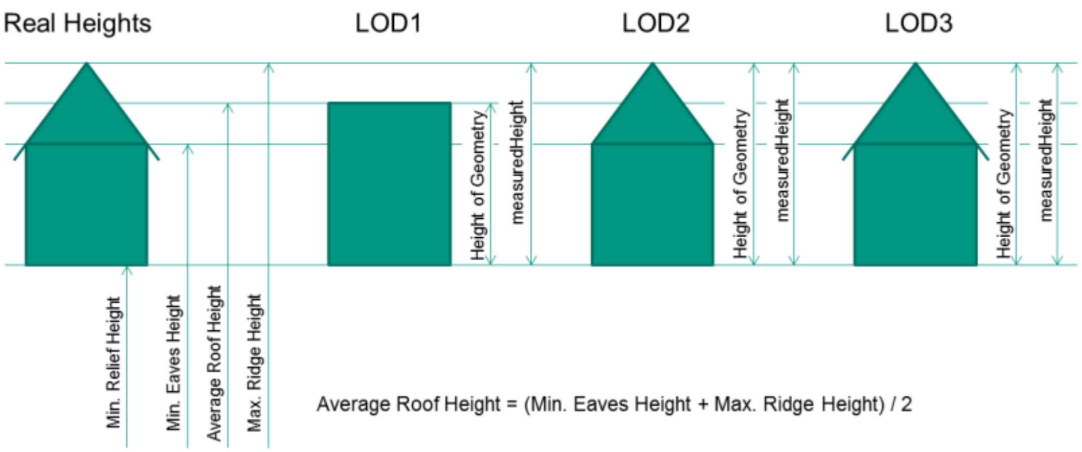

Figure 5.4 Comparison between theoretical real buildings and LoD1/2/3 building model (Courtesy of [27])

Moreover, examining 3dfier's fit results for different types of buildings reveals that if the rooftop variations in height are not particularly pronounced and the roof structure is not complex, 3dfier can achieve highly accurate models. As long as the architectural footprint is precisely drawn, even complex facade structures of the building can be accurately modeled.

Take Hochvolthaus as an example, the building's rooftop is essentially flat, allowing the generated LoD1 model to accurately represent the intended structure of this building. Although 3dfier cannot reconstruct the sloped structures of Hochvolthaus, it successfully recreates its faceted facades and cylindrical features.

In contrast, consider N5, whose rooftop is structured in three tiers. 3dfier can only reconstruct the plane of one tier, resulting in significant discrepancies between the upper portion of the model and the LoD2 ground truth. This illustrates the limitations of 3dfier when dealing with buildings that have complex, multi-level rooftop designs.

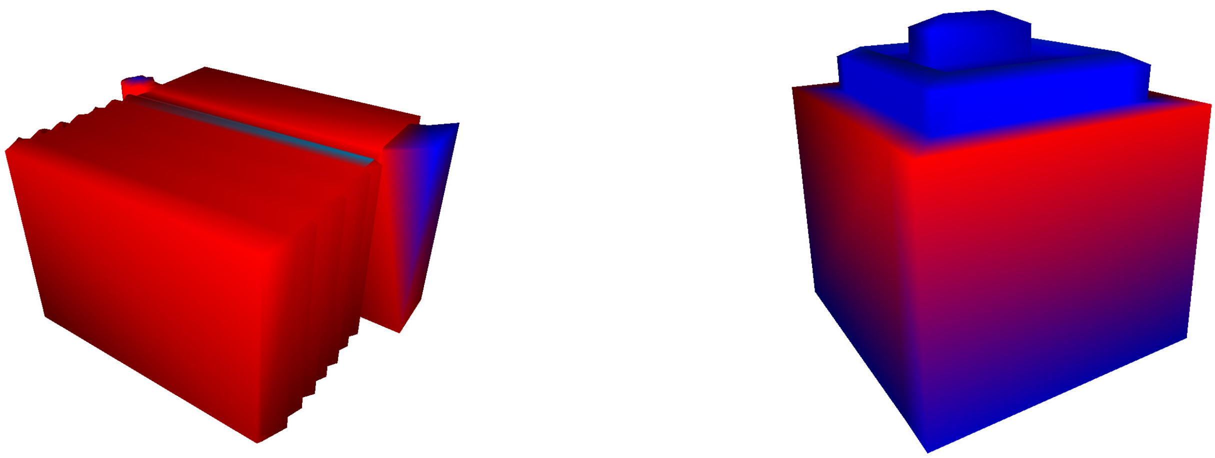

Figure 5.5 LoD2-Groundtruth textured by Hausdorff-Distance with LoD1 from 3dfier (Red:close(0m) | Green:between 0m~0.5m | Blue:0.5m tolerance)Left:Hochvoulthaus; Right:N5-Building

5.2 Polyfit:

Unlike 3dfier, where combining ALS (Airborne Laser Scanning) and MLS (Mobile Laser Scanning) data shows little improvement over using ALS alone, algorithms like PolyFit benefit significantly from this integration. PolyFit relies on detecting and assembling planes from point clouds, and the richer dataset from both ALS and MLS enhances its ability to identify more precise and detailed planes. This results in improved accuracy and completeness of the models.

	ALS+MLS				**ALS**				**MLS**			
Building	**amount**	**max**	**mean**	**RMS**	**amount**	**max**	**mean**	**RMS**	**amount**	**max**	**mean**	**RMS**
FernUNI	18	0.565	0.222	0.284	2	0.537	0.233	0.282	8	5.993	1.216	2.177
Kunstareal	8	0.702	0.356	0.446	3	0.632	0.378	0.421	4	5.395	1.948	2.641
StudiTUM	6	1.406	0.362	0.590	6	1.896	0.589	0.851	3	9.332	4.570	5.438
Hochvolthaus	10	5.766	1.051	1.284	3	13.977	2.825	4.089	0	-	-	-
N5	5	12.519	1.398	2.983	0	-	-	-	2	12.517	7.905	8.493
N8	9	6.558	2.489	3.293	3	34.625	8.835	13.554	10	11.517	2.993	4.126
0503	9	17.215	4.087	6.302	10	22.394	4.280	7.240	2	15.367	3.430	6.057
0507	8	13.888	5.713	7.605	7	9.749	3.949	5.730	4	21.585	13.074	14.923
Haupteingang	7	24.525	4.847	8.132	7	22.599	6.831	9.340	0	-	-	-
total amount	**80**				**41**				**33**			
mean		9.238	2.281	3.435		13.301	3.490	5.188		11.672	5.019	6.265
weighted mean		8.015	3.867	1.535		14.891	15.502	6.084		10.751	16.023	9.940
N1	6	24.011	4.228	7.721	2	17.224	3.048	4.716	12	37.445	11.283	14.951
Audimax					10	15.387	3.145	4.627				

Table 5.1 Comparison of Hausdorff-Distance results of ALS, MLS, and ALS+MLS measurements

total amount = $\sum x_i$ **mean** $= \overline{z(x_i)}$ **weighted mean** $= \frac{\sum z(x_i) \cdot x_i}{\sum x_i}$

Firstly, by combining ALS and MLS data, 80 models were successfully generated, significantly exceeding the 41 models from ALS alone and 33 from MLS alone. This improvement is because the integration of ALS and MLS data compensates for each other's deficiencies, facilitating the formation of more plane combinations.

This ability to fill in missing point cloud areas significantly influences the entire Polyfit process. The process of "Estimate Normals from different amounts of Neighbor Points" can affect the generation of normals, and "Extract Primitives from different minimum support" influences the number of planes generated. These planes in turn determine the difficulty of finding closed point clouds and the quality of the final models produced.

Data from Table 5.1 shows that the models reconstructed from combined ALS+MLS data display significantly better maximum errors, average errors, and RMS(Root Mean Square Error) values compared to those generated from individual datasets. This improvement is particularly evident in moderate-level buildings like Hochvolthaus, N5, and N8, where the point cloud data can cover the entire facade and the buildings are of moderate size, making them suitable for reconstruction with Polyfit. The table data clearly indicates that the Hausdorff distance metrics for models reconstructed using Polyfit with ALS+MLS are markedly better than those using ALS or MLS alone, leading to a substantial enhancement in LoD2 reconstruction results for these types of buildings.

In contrast, for simpler structures like FernUNI, Kunstareal, and StudiTUM, as long as an LoD2 model can be generated, the required planes are few and the possible combinations are relatively fixed due to the simplicity of the structures. Thus, the differences in the Hausdorff distance metrics between models generated with combined ALS+MLS and those with ALS alone are minimal, as both can be controlled within an excellent range, producing almost directly usable LoD2 models. However, the use of MLS data alone can lead to noticeable declines in data quality due to missing rooftop data, often resulting in the truncation of upper parts.

However, for buildings with unique structures such as 0503, 0507, Haupteingang, and N1, their volume, complexity, and the extent of point cloud omissions exceed the capabilities of Polyfit. Even if a similar closed 3D model can be reconstructed, it might only resemble the actual structure in form and might not be directly usable. Therefore, the Hausdorff distance results presented in the table for these buildings are extremely bad. And in the case of building N1, Polyfit is even not able to successfully construct a model within the point cloud.

In PolyFit, two critical parameters—"Estimate Normals from different amounts of Neighbor Points" and "Extract Primitives from different minimum support"—play pivotal roles. The former determines how many neighboring points are used to estimate a point's normals, where a smaller value leads to more points being used to generate normals, thus enhancing the precision of model details. The latter specifies the minimum number of normals required to generate a plan, a smaller value allows for more planes to be generated, facilitating detailed reconstruction of complex structures.

Since each building in this project contains a large number of points, ranging from 25,000 to 272,000, the direct impact of the "Extract Primitives from different minimum support" parameter on the number of planes generated is clear. Successful building reconstruction depends on having a sufficient number of planes and the accurate combination of these planes.

Fine-tuning these parameters demands a deep understanding of the building and scanning data characteristics, requiring operators to adjust parameters for different buildings to get the best reconstruction results. Properly adjusting these parameters can greatly enhance the accuracy and detail of the model, particularly for structurally complex buildings or those with significant missing data sections.

StudiTUM(ALS+MLS)	Extract Primitives from different minimum support					
Estimate Normals	30	50	100	300	500	800
30	✓	✓	×	×	×	×
50	✓	✓	×	×	×	×
100	✓	✓	×	×	×	×
N8 (ALS+MLS)	Extract Primitives from different minimum support					
Estimate Normals	30	50	100	300	500	800
30	×	×	×	✓	✓	✓
50	×	×	×	✓	✓	✓
100	×	×	×	✓	✓	✓

Table 5.2 Hausdorff Results of StudiTUM and N8-building based on ALS+MLS point cloud

Taking StudiTUM and N8 as examples, StudiTUM can only perform checks for plane closure when generating planes based on a maximum of 50 points. Using too many points to search for planes leads to the extraction of too few planes, ultimately preventing the identification of a "waterproof" method for plane closure.

In contrast, N8 requires at least 300 points to generate planes that could potentially result in a reasonable combination of planes. Using a smaller number of points, similar to the approach for StudiTUM where 30 points are used for plane extraction, results in the generation of too many planes. This complexity exceeds Polyfit's computational capabilities, leading to impractical calculations.

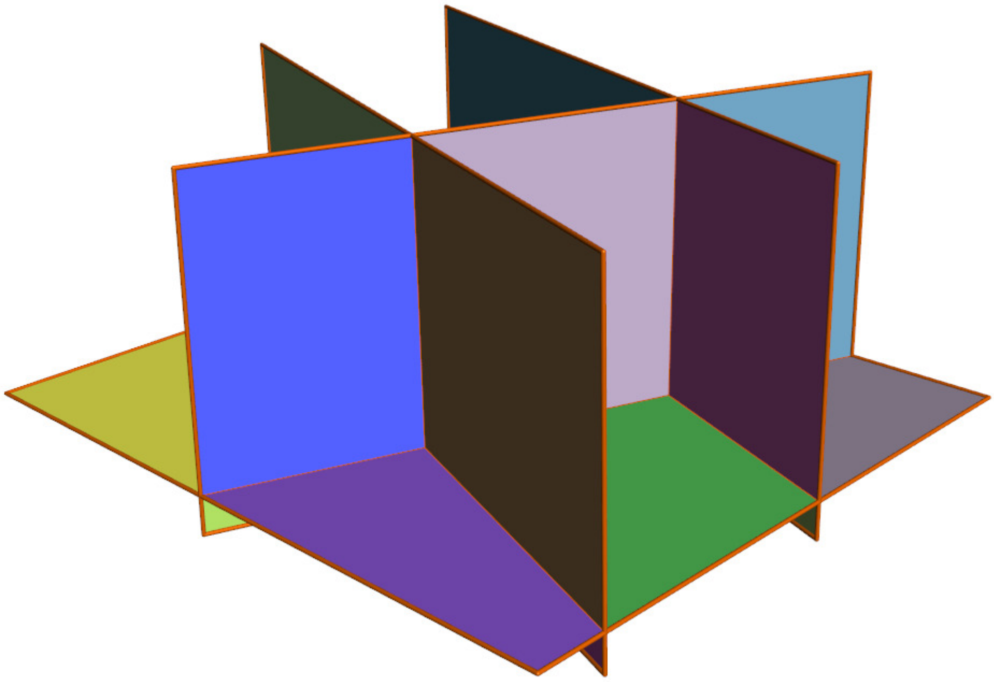

Figure 5.6 StudiTUM in Polyfit, with Estimate Normals set as 50; Extract Primitives set as 100. With only 4 planes is too few for Polyfit to reconstruct a building model

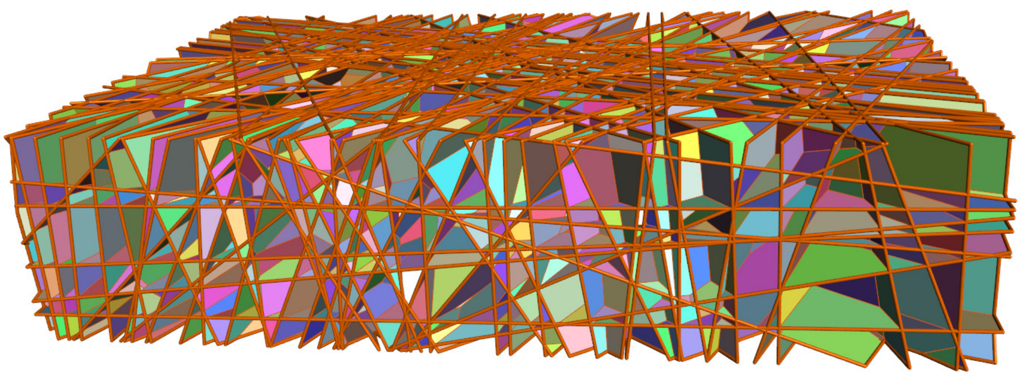

Figure 5.7 N8-building in Polyfit, with Estimate Normals set as 50; Extract Primitives set as 30. With 119 planes is too complicated for Polyfit to reconstruct a building model

6 Conclusion and Outlook

6.1 Conclusion

This study conducts a detailed comparative analysis of Mobile Laser Scanning (MLS) and Airborne Laser Scanning (ALS) technologies to create models at various Levels of Detail (LoD). It aims to improve model accuracy and utility by evaluating tools like 3dfier and Polyfit, integrating these advanced scanning technologies through a robust testing framework that measures performance and assesses the interoperability of ALS and MLS data. The study critically examines each tool's processing capabilities, emphasizing their strengths and limitations in managing urban data complexities. From this project, several key findings have emerged that underscore the varying sensitivities and efficiencies of these technologies in different urban modeling scenarios.

1) 3dfier generates LoD1 models by projecting points onto pre-designated locations using architectural footprints, negating the requirement for highly precise point cloud data. It effectively distinguishes buildings using gml_ids and streamlines rooftop reconstructions using planes. This is critical for large-scale urban modeling, exemplified by 3dfier's ability to segment point clouds and construct variably tall LoD1 models in closely connected buildings, preserving their topological integrity.

2) Polyfit relies on primitives that Mapple extracts for combinations of enclosed planes. According to observations, Polyfit does exceptionally well at reconstructing LoD2 models by extracting 10 to 40 planes. However, it struggles with more intricate structures or point clouds that contain more than 100 planes, and it frequently fails to produce models even after lengthy processing durations.

6.2 Outlook

Since Polyfit's method can further improve roof details and utilizing ALS data with 3dfier already produces outstanding results for LoD1 models, a synergistic combination of the two can be evolved into a more logical approach to generating LoD2 models.

Initially, a method similar to 3dfier can be used to create flat-roofed buildings based on architectural footprints, which serve as the foundation for building facades in the LoD2 models. Subsequently, a Polyfit-like algorithm can reconstruct the structural details of the building's roof. Combining these two elements can form a cohesive whole as the final LoD2 model. This integrated approach not only simplifies the computational process but also optimizes the final model outcome. Such a method is particularly suitable for buildings like N8, which have complex roof structures. With this approach, there's no need to worry about Polyfit generating only the roof structure when using ALS data, as the building's main body can also be reconstructed by 3dfier.

Moreover, since ALS data alone can achieve the same quality of LoD1 models as ALS+MLS data when used with 3dfier, MLS data becomes unnecessary. This approach allows for obtaining high-standard LoD2 models using only ALS data, which could potentially match or exceed the precision of models that Polyfit produces with ALS+MLS data.

However, while MLS data may not capture sufficient rooftop information, it does provide rich architectural facade details. This capability makes MLS data a valuable resource for constructing LoD3 models, offering LoD3 details in capturing facade intricacies that aerial point cloud scanning cannot achieve without time-consuming TLS scans.

The automation of urban architectural modeling remains a topic worth exploring, whether for generating LoD1, LoD2, or LoD3 models, each of which serves unique purposes. While existing tools can effectively automate the reconstruction of large building areas into LoD1 models and individual buildings into LoD2 models, the automated reconstruction of LoD3 models is rarely discussed. The principal challenge lies in the difficulty of distinguishing buildings and planes using only point cloud data as the input.

Further research could explore approaches similar to the use of architectural footprints, incorporating additional external data, such as interior photographic imagery of buildings. Although employing a more diverse set of data sources as inputs increases computational complexity but can reduce the generation of irrelevant planes or confine the creation of planes within a reasonable size range. It can also restrict their topological relationships with unrelated facades, simplifying the computation of the final closed models. This methodological advancement would not only enhance the precision of the models but also extend the utility of point cloud data in architectural modeling across different levels of detail.

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7 Appendix

Appendix

ALS+MLS Hausdorff Distance (RMS)								
FernUNI (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.284
Estimate Normals	30	0.272	0.295	0.281	0.288	0.268	0.277	
	50	0.267	0.284	0.292	0.282	0.284	0.296	
	100	0.261	0.289	0.276	0.296	0.27	0.316	
Kunstareal (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.446
Estimate Normals	30	0.460	0.384	0.466	×	×	×	
	50	0.465	0.443	0.461	×	×	×	
	100	0.426	0.462	×	×	×	×	
StudiTUM (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.590
Estimate Normals	30	0.550	0.525	×	×	×	×	
	50	0.687	0.685	×	×	×	×	
	100	0.555	0.537	×	×	×	×	
Hochvolthaus (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	1.284
Estimate Normals	30	×	×	2.180	1.262	1.129	×	
	50	×	×	1.209	1.050	1.163	1.460	
	100	×	×	1.133	1.138	1.118	×	
N5 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	2.983
Estimate Normals	30	×	1.417	0.894	×	×	×	
	50	×	1.758	×	×	×	×	
	100	×	4.529	6.318	×	×	×	
N8 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	3.293
Estimate Normals	30	×	×	×	3.478	1.402	4.944	
	50	×	×	×	1.705	2.083	4.944	
	100	×	×	×	2.294	5.093	3.691	
0503 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	6.302
Estimate Normals	30	×	×	×	4.640	6.900	8.413	
	50	×	×	×	5.115	4.798	8.481	
	100	×	×	×	4.433	5.455	8.483	
0507 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	7.605
Estimate Normals	30	×	×	×	11.213	6.869	×	
	50	×	×	2.257	3.111	6.911	×	
	100	×	×	7.302	9.578	13.597	×	
Haupteingang (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	8.132
Estimate Normals	30	×	×	×	5.147	8.407	11.175	
	50	×	×	×	5.207	11.518	×	
	100	×	×	×	5.032	10.436	×	
N1 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	7.721
Estimate Normals	30	×	×	×	7.339	8.482	×	
	50	×	×	×	8.163	8.356	×	
	100	×	×	×	7.067	6.919	×	

Table 7.1 Hausdorff-Distance(RMS) of LoD2 model from ALS+MLS point cloud

ALS+MLS Hausdorff Distance (max)

FernUNI (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.565
Estimate Normals	30	0.554	0.568	0.567	0.567	0.567	0.567	
	50	0.553	0.567	0.567	0.567	0.567	0.567	
	100	0.552	0.568	0.568	0.567	0.567	0.567	
Kunstareal (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.702
Estimate Normals	30	0.732	0.546	0.736	×	×	×	
	50	0.732	0.672	0.732	×	×	×	
	100	0.733	0.732	×	×	×	×	
StudiTUM (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	1.406
Estimate Normals	30	1.438	1.375	×	×	×	×	
	50	1.406	1.438	×	×	×	×	
	100	1.406	1.375	×	×	×	×	
Hochvolthaus (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	5.766
Estimate Normals	30	×	×	5.832	5.467	5.602	×	
	50	×	×	5.654	5.745	5.745	7.126	
	100	×	×	5.702	5.510	5.278	×	
N5 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	12.519
Estimate Normals	30	×	4.438	3.504	×	×	×	
	50	×	6.397	×	×	×	×	
	100	×	23.443	24.814	×	×	×	
N8 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	6.558
Estimate Normals	30	×	×	×	7.249	2.812	8.406	
	50	×	×	×	6.750	4.500	8.406	
	100	×	×	×	4.680	8.863	7.359	
0503 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	17.215
Estimate Normals	30	×	×	×	16.312	21.330	16.765	
	50	×	×	×	16.911	16.483	17.279	
	100	×	×	×	16.430	16.421	17.004	
0507 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	13.888
Estimate Normals	30	×	×	×	19.239	11.697	×	
	50	×	×	6.266	6.256	13.983	×	
	100	×	×	11.522	17.614	24.530	×	
Haupteingang (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	24.525
Estimate Normals	30	×	×	×	16.117	28.014	31.448	
	50	×	×	×	17.122	31.558	×	
	100	×	×	×	15.982	31.431	×	
N1 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	24.011
Estimate Normals	30	×	×	×	24.459	24.463	×	
	50	×	×	×	24.453	24.476	×	
	100	×	×	×	24.422	21.795	×	

Table 7.2 Hausdorff-Distance(max) of LoD2 model from ALS+MLS point cloud

ALS+MLS Hausdorff Distance (mean)								
FernUNI (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.222
Estimate Normals	30	0.218	0.239	0.226	0.228	0.199	0.209	
	50	0.205	0.217	0.221	0.223	0.227	0.237	
	100	0.207	0.229	0.211	0.245	0.193	0.261	
Kunstareal (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.356
Estimate Normals	30	0.355	0.347	0.376	×	×	×	
	50	0.377	0.356	0.357	×	×	×	
	100	0.321	0.359	×	×	×	×	
StudiTUM (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.362
Estimate Normals	30	0.310	0.293	×	×	×	×	
	50	0.477	0.479	×	×	×	×	
	100	0.317	0.298	×	×	×	×	
Hochvolthaus (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	1.051
Estimate Normals	30	×	×	1.881	1.047	0.914	×	
	50	×	×	0.984	0.900	0.930	1.067	
	100	×	×	0.940	0.929	0.922	×	
N5 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	1.398
Estimate Normals	30	×	0.762	0.523	×	×	×	
	50	×	1.185	×	×	×	×	
	100	×	1.593	2.928	×	×	×	
N8 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	2.489
Estimate Normals	30	×	×	×	2.526	1.083	3.804	
	50	×	×	×	1.302	1.448	3.804	
	100	×	×	×	1.784	3.902	2.746	
0503 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.087
Estimate Normals	30	×	×	×	2.905	4.373	5.76	
	50	×	×	×	3.22	2.839	5.754	
	100	×	×	×	2.61	3.539	5.78	
0507 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	5.713
Estimate Normals	30	×	×	×	7.973	5.148	×	
	50	×	×	1.115	2.500	4.996	×	
	100	×	×	6.541	6.826	10.605	×	
Haupteingang (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.847
Estimate Normals	30	×	×	×	3.037	5.190	6.523	
	50	×	×	×	3.050	6.942	×	
	100	×	×	×	2.936	6.251	×	
N1 (ALS+MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.228
Estimate Normals	30	×	×	×	3.795	4.889	×	
	50	×	×	×	4.513	5.112	×	
	100	×	×	×	3.391	3.668	×	

Table 7.3 Hausdorff-Distance(mean) of LoD2 model from ALS+MLS point cloud

ALS Hausdorff Distance (RMS)

FernUNI (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.282
Estimate Normals	30	0.263	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	0.300	×	×	×	×	×	
Kunstareal (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.421
Estimate Normals	30	0.425	×	×	×	×	×	
	50	0.412	×	×	×	×	×	
	100	0.425	×	×	×	×	×	
StudiTUM (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.851
Estimate Normals	30	0.784	0.807	×	×	×	×	
	50	0.706	0.879	×	×	×	×	
	100	1.199	0.730	×	×	×	×	
Hochvolthaus (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.089
Estimate Normals	30	×	×	×	×	×	×	
	50	4.102	×	×	×	×	×	
	100	4.019	4.146	×	×	×	×	
N5 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N8 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	13.554
Estimate Normals	30	×	×	12.016	×	×	×	
	50	×	×	26.599	×	×	×	
	100	×	×	2.048	×	×	×	
0503 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	7.240
Estimate Normals	30	×	×	4.970	5.174	9.095	×	
	50	×	×	5.704	5.086	9.120	13.246	
	100	×	4.464	×	7.152	8.387	×	
0507 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	5.730
Estimate Normals	30	5.341	6.050	6.043	×	×	×	
	50	5.860	6.447	5.506	×	×	×	
	100	×	×	4.862	×	×	×	
Haupteingang (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	9.340
Estimate Normals	30	×	×	4.079	5.505	19.774	×	
	50	×	×	×	4.686	5.917	×	
	100	×	×	×	5.830	19.586	×	
N1 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.716
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	4.716	4.715	×	×	×	
Audimax (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.627
Estimate Normals	30	×	2.578	4.568	6.358	8.468	×	
	50	×	2.503	4.146	6.955	4.155	×	
	100	×	×	2.786	3.748	×	×	

Table 7.4 Hausdorff-Distance(RMS) of LoD2 model from ALS point cloud

ALS Hausdorff Distance (max)

FernUNI (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.537
Estimate Normals	30	0.517	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	0.556	×	×	×	×	×	
Kunstareal (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.632
Estimate Normals	30	0.633	×	×	×	×	×	
	50	0.633	×	×	×	×	×	
	100	0.631	×	×	×	×	×	
StudiTUM (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	1.896
Estimate Normals	30	2.197	1.746	×	×	×	×	
	50	1.796	1.781	×	×	×	×	
	100	2.009	1.844	×	×	×	×	
Hochvolthaus (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	13.977
Estimate Normals	30	×	×	×	×	×	×	
	50	13.995	×	×	×	×	×	
	100	13.880	14.055	×	×	×	×	
N5 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N8 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	34.625
Estimate Normals	30	×	×	33.546	×	×	×	
	50	×	×	61.197	×	×	×	
	100	×	×	9.132	×	×	×	
0503 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	22.394
Estimate Normals	30	×	×	15.750	18.125	28.717	×	
	50	×	×	23.155	17.875	28.748	25.122	
	100	×	18.136	×	20.472	27.835	×	
0507 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	9.749
Estimate Normals	30	10.468	10.468	10.468	×	×	×	
	50	10.272	6.452	10.203	×	×	×	
	100	×	×	9.910	×	×	×	
Haupteingang (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	22.599
Estimate Normals	30	×	×	13.808	14.846	41.026	×	
	50	×	×	×	16.061	15.994	×	
	100	×	×	×	15.994	40.466	×	
N1 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	17.224
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	17.225	17.223	×	×	×	
Audimax (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	15.387
Estimate Normals	30	×	11.288	15.234	21.014	24.425	×	
	50	×	10.657	15.600	20.153	11.629	×	
	100	×	×	11.585	12.285	×	×	

Table 7.5 Hausdorff-Distance(max) of LoD2 model from ALS point cloud

ALS Hausdorff Distance (mean)

FernUNI (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.223
Estimate Normals	30	0.200	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	0.245	×	×	×	×	×	
Kunstareal (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.378
Estimate Normals	30	0.381	×	×	×	×	×	
	50	0.366	×	×	×	×	×	
	100	0.386	×	×	×	×	×	
StudiTUM (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	0.589
Estimate Normals	30	0.511	0.595	×	×	×	×	
	50	0.455	0.667	×	×	×	×	
	100	0.867	0.438	×	×	×	×	
Hochvolthaus (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	2.825
Estimate Normals	30	×	×	×	×	×	×	
	50	2.823	×	×	×	×	×	
	100	2.751	2.901	×	×	×	×	
N5 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N8 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	8.835
Estimate Normals	30	×	×	6.667	×	×	×	
	50	×	×	18.515	×	×	×	
	100	×	×	1.324	×	×	×	
0503 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.280
Estimate Normals	30	×	×	3.077	3.060	5.143	×	
	50	×	×	2.897	3.022	5.197	9.545	
	100	×	2.354	×	4.083	4.420	×	
0507 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	3.949
Estimate Normals	30	3.901	4.673	4.664	×	×	×	
	50	4.544	2.270	4.216	×	×	×	
	100	×	×	3.376	×	×	×	
Haupteingang (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	6.831
Estimate Normals	30	×	×	2.564	3.468	15.852	×	
	50	×	×	×	3.003	3.672	×	
	100	×	×	×	3.605	15.65	×	
N1 (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	3.048
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	3.046	3.050	×	×	×	
Audimax (ALS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	3.145
Estimate Normals	30	×	1.693	2.966	4.269	6.074	×	
	50	×	1.749	2.482	4.885	3.049	×	
	100	×	×	1.842	2.437	×	×	

Table 7.6 Hausdorff-Distance(mean) of LoD2 model from ALS point cloud

MLS Hausdorff Distance (RMS)

FernUNI (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	2.177
Estimate Normals	30	0.777	1.700	×	×	×	×	
	50	1.128	1.831	3.250	×	×	×	
	100	0.765	1.877	6.086	×	×	×	
Kunstareal (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	2.641
Estimate Normals	30	1.367	1.372	×	×	×	×	
	50	3.881	3.944	×	×	×	×	
	100	×	×	×	×	×	×	
StudiTUM (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	5.438
Estimate Normals	30	3.870	×	×	×	×	×	
	50	5.662	×	×	×	×	×	
	100	6.781	×	×	×	×	×	
Hochvolthaus (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N5 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	8.493
Estimate Normals	30	×	×	8.778	×	×	×	
	50	×	×	8.207	×	×	×	
	100	×	×	×	×	×	×	
N8 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.126
Estimate Normals	30	×	×	8.667	2.998	3.363	4.402	
	50	×	×	×	3.995	3.418	4.371	
	100	×	×	×	3.049	3.502	3.493	
0503 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	6.057
Estimate Normals	30	×	×	6.221	×	×	×	
	50	×	×	×	×	×	×	
	100	×	5.892	×	×	×	×	
0507 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	14.923
Estimate Normals	30	×	×	×	18.570	14.037	×	
	50	×	×	×	13.366	×	×	
	100	×	×	×	13.719	×	×	
Haupteingang (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N1 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	14.951
Estimate Normals	30	×	×	12.653	12.683	14.860	14.746	
	50	×	×	14.690	14.999	14.903	14.835	
	100	×	×	13.229	17.525	14.846	19.444	

Table 7.7 Hausdorff-Distance(RMS) of LoD2 model from MLS point cloud

MLS Hausdorff Distance (max)								
FernUNI (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	5.993
Estimate Normals	30	3.020	6.000	×	×	×	×	
	50	4.188	6.500	7.715	×	×	×	
	100	2.986	6.750	10.781	×	×	×	
Kunstareal (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	5.395
Estimate Normals	30	3.421	3.420	×	×	×	×	
	50	7.344	7.393	×	×	×	×	
	100	×	×	×	×	×	×	
StudiTUM (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	9.332
Estimate Normals	30	8.962	×	×	×	×	×	
	50	9.260	×	×	×	×	×	
	100	9.773	×	×	×	×	×	
Hochvolthaus (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N5 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	12.517
Estimate Normals	30	×	×	12.675	×	×	×	
	50	×	×	12.359	×	×	×	
	100	×	×	×	×	×	×	
N8 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	11.517
Estimate Normals	30	×	×	25.219	5.316	10.063	12.190	
	50	×	×	×	7.677	10.091	12.150	
	100	×	×	×	10.870	10.807	10.782	
0503 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	15.367
Estimate Normals	30	×	×	16.337	×	×	×	
	50	×	×	×	×	×	×	
	100	×	14.396	×	×	×	×	
0507 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	21.585
Estimate Normals	30	×	×	×	25.551	20.838	×	
	50	×	×	×	19.855	×	×	
	100	×	×	×	20.096	×	×	
Haupteingang (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N1 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	37.445
Estimate Normals	30	×	×	36.935	35.474	35.474	35.474	
	50	×	×	36.983	44.473	35.476	35.476	
	100	×	×	35.963	35.530	36.551	45.530	

Table 7.8 Hausdorff-Distance(max) of LoD2 model from MLS point cloud

MLS Hausdorff Distance (mean)

FernUNI (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	1.216
Estimate Normals	30	0.337	0.680	×	×	×	×	
	50	0.545	0.757	1.780	×	×	×	
	100	0.317	0.872	4.439	×	×	×	
Kunstareal (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	1.948
Estimate Normals	30	0.865	0.891	×	×	×	×	
	50	2.971	3.063	×	×	×	×	
	100	×	×	×	×	×	×	
StudiTUM (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	4.570
Estimate Normals	30	2.673	×	×	×	×	×	
	50	4.740	×	×	×	×	×	
	100	6.297	×	×	×	×	×	
Hochvolthaus (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N5 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	7.905
Estimate Normals	30	×	×	8.257	×	×	×	
	50	×	×	7.552	×	×	×	
	100	×	×	×	×	×	×	
N8 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	2.993
Estimate Normals	30	×	×	5.994	2.369	2.289	3.370	
	50	×	×	×	3.113	2.377	3.325	
	100	×	×	×	2.020	2.541	2.535	
0503 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	3.430
Estimate Normals	30	×	×	3.535	×	×	×	
	50	×	×	×	×	×	×	
	100	×	3.325	×	×	×	×	
0507 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	13.074
Estimate Normals	30	×	×	×	16.177	12.309	×	
	50	×	×	×	11.608	×	×	
	100	×	×	×	12.200	×	×	
Haupteingang (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	
Estimate Normals	30	×	×	×	×	×	×	
	50	×	×	×	×	×	×	
	100	×	×	×	×	×	×	
N1 (MLS)		Extract Primitives from different minimum support						Average:
		30	50	100	300	500	800	11.283
Estimate Normals	30	×	×	7.801	8.520	11.757	11.492	
	50	×	×	11.275	9.883	11.784	11.589	
	100	×	×	9.094	14.563	11.728	15.909	

Table 7.9 Hausdorff-Distance(mean) of LoD2 model from MLS point cloud