3D building modelling using dense point clouds from UAV

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ABSTRACT

3D building reconstruction can be done from both the lidar and image-based point clouds, however, the lidar point clouds has dominated the research giving the 3D buildings reconstruction from aerial images point clouds less attention. The UAV images can be acquired at low cost, the workflow can be automated with minimal technical knowhow limitation. This promotes the necessity to understand and question to what extent the 3D buildings from UAV point clouds are complete and correct from data processing to parameter settings. Apart from the cost and the challenges of 3D points capture, the main problem is the reconstruction of a 3D building from data which is affected by many factors like point density, occlusions and vegetation among others.

This research deals with the modelling of 3D buildings from UAV image data, and its comparison with the 3D buildings from airborne laser data. The research starts with analysing the quality of the input data from UAV imagery and airborne laser data in terms of point density and point noise, in relation to setting parameter later in the process for 3D building modelling. One of the crucial steps is a proper segmentation into planar roof faces. Optimal parameter settings are analysed for UAV image-based point clouds and laser scanner point clouds. An automatic data driven model approach to 3D building reconstruction from UAV point louds is used from B. Xiong et al 2016, followed by a façade detection step to capture the real extent of the building where there is a roof overhang.

The UAV point density can be varied from 2500, 350 and 80 pnts/m^2 by the Pix4Dmapper image matching, algorithm and choice of which density to use, depends on the size of features on the roof. The proposed algorithm is presented by use of UAV image-based point clouds of about 350pnts/m^2 and laser scanner point clouds of about 15pnts/m^2. The quality of the point clouds and that of the reconstructed models is compared to that of the airborne laser scanning as the reference data. The same UAV images edge information of the buildings has been used to support the 3D reconstruction and restrict the extent of the boundary and reprojection of the walls.

Key words: UAV images, Image matching, UAV dense point clouds, ALS point clouds, Segmentation, 3D Building reconstruction/Modelling.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Motivation and statement problem

3D buildings are very important in urban planning, emergency response, disaster management, and decision making (Xiao, Gerke, & Vosselman, 2012). They can be applied to urban parameters for monitoring and evaluation (i.e. volumetric data), monitoring built-up areas and illegal buildings, and indicators of city planning (Rebelo, Rodrigues, Tenedório, Goncalves, & Marnoto, 2015). 3D buildings intend to show the geometry and the appearance of reality, they can allow us to view at the city as it is now, how it looked in the past, and how it will look probably look in future. There exist different approaches to 3D building modelling and many researches have been done, however, as Haala & Kada (2010) points out, there is a lot of thirst in the 3D modelling and the field is still a very active area of research.

For a considerable period now, Photogrammetry has been the mother of 3D buildings reconstruction by use of stereo images, but this traditional manual stereo pair feature extraction is tedious and time consuming for large areas with many buildings. Then about two decades ago came the Airborne laser scanning (ALS) also known as lidar (Light detection and ranging) and photogrammetric computer vision 3D point clouds from airborne imagery which can automatically extract 3D buildings (Malihi, Valadan Zoej, Hahn, Mokhtarzade, & Arefi, 2016). The advanced technology in ALS and stereo-image matching has really optimized time taken to extracting the 3D buildings compared to the manual feature extraction from stereo images, but the problem has been the reconstruction of a 3D buildings which represent the reality on the ground.

The ALS for years now has dominated the acquisition of Digital Elevation Models (DEM). ALS point clouds are accurate, give ready 3D data, and can penetrate in vegetation. It has been used to automatically generate 3D building models by the fusion with 2D maps, however, problematic areas occur when there is lack of data information. The main drawback of ALS point clouds is that it costly to acquire and can capture only the roof and other parts of a building which are only visible from an aerial perspective and those visible from a terrestrial perspective are not captured like the areas underside the balconies and the wall of the building which are occluded. ALS cannot record data on slate roofs, roof covered with water, glass materials, the beam can also be diverted by solar panels, and point density is not that dense depending on many parameters of the ALS scanner. Moreover, there is lack of accuracy at the edge of the building due to laser sampling. Maltezos & Ioannidis (2015) argues that, lidar point clouds give false results as it confuses buildings with smooth canopy.

Meanwhile, image-based collection is being revived as a suitable alternative. Unmanned aerial vehicles (UAV), also known as drones are accepted as a low cost and high-efficiency techniques in the acquisition of object geometries. It is also recognized as possible midway option between higher resolution ground-based images and the lower resolution data acquisition from airborne and satellite. UAVs has the advantage over the lidar or other platforms because it can be manipulated for oblique images, multi-overlaps and resolution. UAVs can capture the facades of a building and get the true geometry of the building thus obtaining the real extent which tends to be wrongly estimated by roof edge due to the overhanging parts of the roof.

a) *UAV Nadir image*	b) *UAVs point clouds*	c) *ALS point clouds*

Figure 1-1: a) UAV nadir images; b) UAVs point clouds; c) ALS point clouds

Limitations of UAVs can be separated into three broad categories, namely, **operational restrictions;** (such as weather condition, terrain, spatial coverage, radio connection, landing services) **political readiness;** (such as public approval, safety measures) and **regulation restrictions;** (such as privacy, reliability, region coverage, flying height). Aerial imagery has shortcomings for dense point clouds generation due to occlusion, shadows and poor contrast (Li et al., 2013). Although both the datasets suffer some similar problems like occlusion, from literature review it can be argued that UAVs image-based point clouds data is becoming more an effective alternative to ALS point clouds data. 3D buildings from UAVs can be improved by enhancing roof boundary by use of edge information from images. It can also be improved by merging the imagery building outlines, point clouds roof boundary and the walls outline to extract the real extent of the building. It is possible for drones equipped with a GPS (Global positioning System), digital camera and a powerful computer to survey with an accuracy of 1 to 2cm (Corrigan & Ads, 2017).

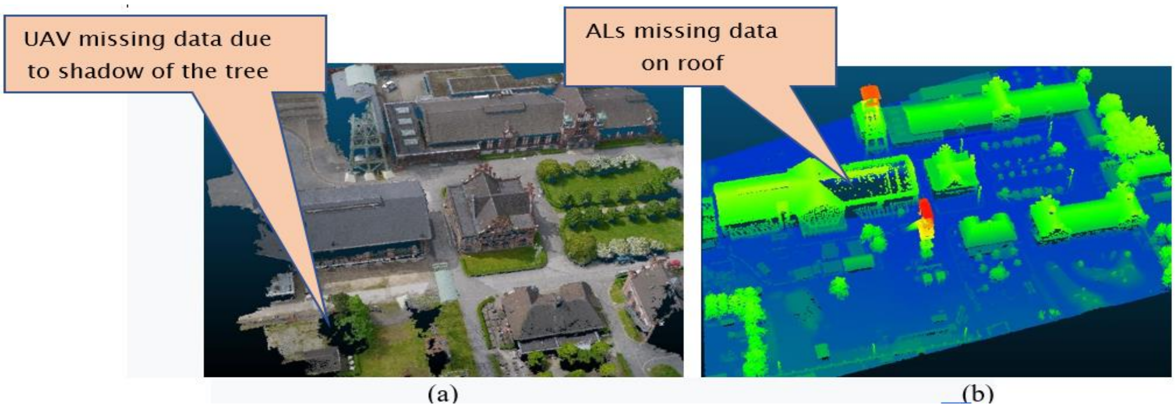


Figure 1-2 a):Some of UAVs point clouds missing due to shadows of the tree and on ALS point clouds the same area has data; b): ALS point missing on the roof but on the same roof on the UAV, the points are captured. This can also happen at the edges where there are tree canopies or occlusion for both datasets.

Many approached to 3D building modelling has been conducted and the development of a fully automated algorithm is still a challenge to many researchers (Haala & Kada, 2010). Xiong, (2014) summarizes the main challenges of 3D building modelling as follows:

- **Complex scenes** - The environment to which the buildings are found is a mixer of many objects thus hard to distinguish.
- **Complex buildings shapes -** Some building has complicated shapes and a lot of furniture on the roof.
- **Complex boundaries –** Some incomplete shapes missing due to missing 3D points.
- **Lack of data –**These are caused by occlusion, slate roofs, water on roofs, shadows for the UAVs, and so on.

The main motivation is that UAVs have recently gained popularity in several applications. These instruments can obtain high-resolution imagery at a lower cost and more flexible acquisition than traditional aerial or satellite imagery. The developments in computer vision and photogrammetry allow for the extraction of geometrically accurate point clouds from overlapping imagery and automatic scene interpretation, thus it is turning to be a cheaper alternative to ALS. The motivation is more triggered by the increased quality of digital cameras, flight path planning flexibility as well as the innovation in image matching algorithm like semi-Global matching (SGM) which is a pixel-wise matching. Dense image matching according to recent tests have already demonstrated a valid alternative to ALS although it has its own challenges. According to (Remondino, F., Spera, M. G., Nocerino, E., Menna, F., & Nex, F. 2014), Image matching is one of the keys to 3D modelling. They explained some of the challenges of images matching as ambiguity, repetitive structures, occlusions, textureless regions and so on. From the above literature review, **table 1.1** is a summary of the limitations in the ALS data capture and UAV point clouds extraction.

Table 1-1 comparison of UAV and ALS point clouds limitations

LIMITATIONS	ALS DATA CAPTURE	UAVs POINT CLOUDS EXTRACTION
cost	Costly in terms of equipment	Drones and cameras becoming Cheaper
Facades captured	Only Aerial perspective	All for multi-view oblique plus nadir
Slate roofs	x	
Roof with water	x	x
Glass materials	x	x
Beam divergence by solar panels, sampling	x	
Shadows		x
Occlusions	x	x
Ambiguity, repetitive structure, textureless regions, **poor contrast, etc.**		Problems in Image matching

1.2. Research identification

This research is aimed at 3D building modelling from UAV dense point clouds and is composed of five main tasks: UAV dense matching pre-processing, 2D information from the generated orthomosaic, segmentation, building reconstruction and evaluation. The features of interest are the buildings roofs and walls and their automatic detection is done by identifying an algorithm that can integrate the dense point clouds, image information and the facades. Haala & Kada, (2010) has given an update of the current state of the art and many approaches to 3D building reconstructing from laser and aerial images, and many algorithms use cadastral data to define the roof boundary and generate walls. This research will also focus on the real extent of buildings and use of the images information to enhance the roof boundaries.

1.2.1. Research objectives

The main objective of this research is to automatically reconstruct 3D buildings models of level of details (LOD2) with dense point clouds from UAV images as compared to ALS , how to improve on some of the problems of ALS data and integrate the roof segments, facades and 2D building information from UAV images to improve the location of the existing building outlines.

Specific Objectives:

1. To evaluate the UAV point clouds as an alternative automatic 3D building modelling as compared to the laser data.
2. To evaluate the potentialities of accuracy and completeness of 3D building modelling from UAV point clouds.

3. To integrate UAV point clouds, images and facades to accurately define the real extent of the buildings.
4. To assess an algorithm that can automatically detect whether roof segments are complete.
5. To evaluate the improvement of 3D buildings from a combination of multi-view and oblique UAV images as compared to lidar point clouds.

1.2.2. Research questions

1. Are the 3D building models from UAV point clouds more cost effective and accurate enough to replace the lidar point clouds?
2. To what extent can UAV dense point clouds reconstruct a better 3D building model as compared to lidar point clouds?
3. Can facades generated from UAV point clouds improve the geometry of the 3D building?
4. What is the best algorithm to reconstruct a correct and true to reality 3D building model that meets the purpose of many application?
5. What are the requirements for the generation of an optimal UAVs point clouds, and how can this be translated to the flight path planning?

1.2.3. Innovation aimed at

The idea behind this research is to:

- To see/ find out to what extent UAV point clouds produce better 3D building as compared to ALS data.
- To enhance roof boundary by using the edge information from images considering the lack of data challenges and the noise of laser and photogrammetric data at the edges.
- Automatic detection of the facades to determine real extent of the building

1.3. Thesis structure

This research paper is organized as follows, This section explains the motivation and problem statement, research objectives and research questions. Section 2 describes the Image matching algorithm and state of the arts in related 3D building reconstruction work using different sources of point clouds. Section 3 explains the data used and their source. Section 4 the whole methodology workflow from UAV point clouds to the final 3D buildings reconstruction and the prodecures of assessing the UAV data quality is described. Section 5 is results and discussions, and finally section 6 concludes the research and gives some recomendations.

2. LITERITURE REVIEW

2.1. Image matching

Image matching is a sub-domain of computer vision and focuses on finding similarities in images and matches them. Stereo image matching is used to searching the corresponded pixels in a pair of images allowing 3D reconstruction by triangulation using the known interior and exterior orientation parameters (Remondino, F., Spera, M. G., Nocerino, E., Menna, F., & Nex, F. 2014) . Widyaningrum & Gorte, (2017) describes the structure from motion (SfM) as one technique of image matching by estimating the 3D geometry (structure) and camera pose (motion). They go further to describe how it works, it computes relative projection geometry and a set of sparse 3D points simultaneously. SfM extracts corresponding image features from a series of stereo pairs taken by a moving camera around a scene, the algorithm detects and describes local features for each image then matches them throughout the multiple images as two-dimensional (2D) points. The matched points are then used as an input and the SfM computes the position of those points in model space and 3D point clouds are produced representing the geometry of the scene by triangulation using the interior and exterior parameters of the taking camera.

2.2. Building reconstruction

For two decades now lidar and aerial images point clouds has been the two main type of data for automatic 3D building reconstruction with different level of details (LOD) and using the two main types of approached namely model-driven and data-driven. 3D Buildings automatic detection has been done already from aerial images in earlier research. Xiao et al., (2012) they used oblique airborne images, façade positioning with same view direction were used to recognize buildings and with one key assumption in the method was that facades are a composition of vertical planes

Tutzauer & Haala, (2015) used a combination method of dense point clouds from mobile and aerial images to reconstruct and enrich the building facades, they used Grammar-based approach for the building reconstruction in parts which were not covered by the images. Another approach was applied by Verdie, Lafarge, & Alliez (2015) they used multiple classification of building categories like ground, roofs, or façades. Zebedin, Bauer, Karner, & Bischof, (2008); Rouhani, Lafarge, & Alliez, (2017) with multi-view geometry techniques and multi-view stereo images introduced a Markov Random Field-based approach which segmented textured meshes for urban classes which clearly separated ground, buildings and trees. The input mesh was partitioned into small cluster from which geometric and photometric features are computed.

Many similar approaches of 3D buildings using UAV images have been applied by B. Xiong, Oude Elberink, & Vosselman, (2014), they used free parameter algorithm as an alternative to erroneous roof topology graphs and model-driven method. It took noisy photogrammetric point clouds and existing cadastral maps as the inputs and map acted as the constrains to the roof boundaries and projected the point clouds to the map boundaries to construct the walls. Vacca, Dessì, & Sacco (2017) in particular they studied the accuracy gains achieved in surveying and compared the accuracy in height, area, and volume of the dimensions of the 3D building from UAV nadir and oblique images. Chen, Chen, Deng, Duan, & Zhou, (2016) did an automatic change detection for urban buildings using UAV images and dense point clouds. As it can be observed from literature review over the last few decades, a large number Of building detection techniques have been reported. Haala & Kada, (2010) gives an update of the current state of the art to 3D building reconstruction from laser, aerial images to a combination of the two.

3. STUDY AREA AND MATERIALS

3.1. Study areas

3.1.1. Study area one and dataset

The Study area one was **Nunspeet** a municipality in the central Netherlands-Approximately 52° 22' 20" N 5° 47' 16"E. The area was surveyed first with aerial laser scanner on **figure 3-1** left-image and later with UAV, right-image. The time difference in data acquisition shows some buildings development in the UAV data which are not in the ALS data (Red circle). The building are simple gable roof,without complicated roofs, and the buildings cannot be classified as stall buildings but residecial building with mostly first floor.

UAV Images

312 UAV images covered an area of about 4.4 Hectares and the flight was a nadir covering about 35 main buildings. Camera information was as follows:

Camera model was EP3_17.0_4032x3024 (RGB) with image resolution of 4032*3024, focal length of 16.7095 (mm), sensor size of 17.3*12.975(mm), pixel size of 4.29068(µm) and average GSD of 1.65(cm). The flying height was about 62 m with a forward overlap of 85% and a side overlap of the same magnitude.

Reference data

AHN is a lidar point clouds data covering the Netherland area and stands for Actueel Hoogtebestand Nederland. It is provided as an open data source in Publieke Dienstverlening op de Kaart (PDOK). The AHN lidar data in this research was used as reference, had a point density of about 15 pnts/m² and was clipped to the same size as the UAV data.

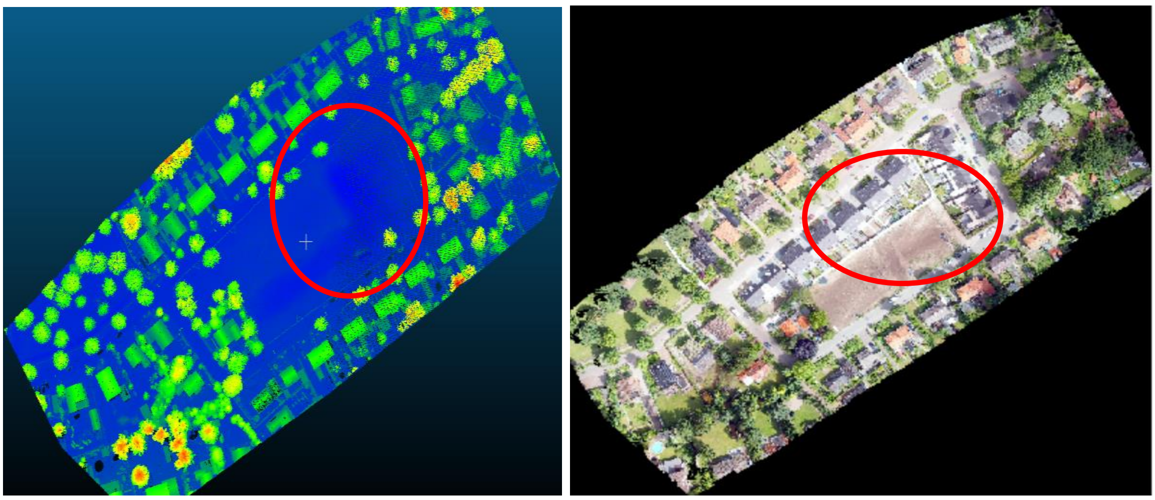


Figure 3-1 Left; ALS data; Right: UAV Orthomosaic image

3.1.2. Study area two and dataset

The study area two was L'Aquila in Italy around 42° 20' 40"N, 13° 23' 38"E **(figure3-2).** The area had only the UAV images and no laser scanner data for comparison, it had both tall and normal buildings, otherwise there could not have been the dataset one choice if there was lidar data. The choice for this area was to realize object 3 of this research. The area had five different flights: Nadir + 4 oblique (North, East, South, west- cardinal directions). This was done to ensure that all the buildings in the area were captured from 360 degrees view. The GDS in the nadir was 2cm and higher for the oblique. The data was captured 2016 with Canon D600 camera using Aibotix drone. The flying height was on average 60m with a forwardlap of 80% and sidelap of 60%. The area had buildings with roof hang and since the images were taken from all the views, it was possible to get a complete capture of all the building sides.

Figure 3-2 L'Aquila one of oblique images to show the area

3.1.3. Study area three and dataset

The study area 3 was **City Hall Dortmund- Germany about** 51° 30' 39"N, 7° 27' 58.40"E **(figure 3-3).** The area was surveyed with UAV, terrestrial images as well as terrestrial laser scanner. The UAV images was acquired June 14th, 2014, with GSD ranging from 1 to 3 cm. The images were both oblique (forwardlap75%, sidelap 85%) and nadir (forwardlap85%, sidelap 85%). This was only one building and 0ver 300 images were captured.

source: ISPRS benchmark for multi-platform photogrammetry.

The ideal behind this building was to realize **objective 5** in this research and to see how many point clouds one big building can have and what are the limitations in the proposed algorithm which can process only 7Million point clouds and what should be done to reduce the point clouds.

Figure 3-3 City Hall Dortmund; One of the oblique images showing part of the building

4. METHODOLOGY

4.1. Method adopted

4.1.1. Proposed methodology

Many algorithms used on photogrammetric point clouds 3D buildings reconstruction has very little difference on the algorithms used in ALS. Despite the ALS being the dominant data source, one of its major challenges is data regarding the building outlines and the walls. Many approaches of the 3D building modelling have been approached by simple connection of the roof to the ground by vertical wall. The methodology proposed in this research is an automatic 3D building reconstruction algorithm by (Xiong, B, Oude Elberink, S.J. and Vosselman, 2016) . First the idea was introduced in (B. Xiong et al., 2014) without footprint maps and later integrated into map partitions in 2016. It takes the point clouds and the existing 2D map boundary as inputs to reconstruct the 3D building.

It starts with decomposing a roof into layers at different heights, and a contour is derived for each layer and snapped to the footprint maps (2D building edge information in this case). The roof layers are derived by segmentation from component analysis. After component analysis to segment the point clouds which are not connected in height into roof layers, the following takes place:

1. The algorithm searches the planar roof patches and the points connecting the patches and group them as structuring points and boundaries
2. The 2D building outlines restricts the building region and the roof patches are snapped to meet the polygon regularities.
3. The structuring points and boundaries provide only the inner corners and boundaries of the roof.
4. The outer corners and boundaries are derived from the simplified contour of all the points of the roof layers.
5. The roof models are achieved by sequential connecting all the boundary lines for each roof surface and projecting the outer boundaries onto ground as walls.

For more details about how this method works, is explain in (B. Xiong et al., 2014) and (B. Xiong et al., 2016).

4.1.2. 2D building outlines from the orthomosaic generated from the same UAVs images

Cadastral maps were used in 3D buildings reconstruction in the proposed methodology, but this research proposed building outlines from the same UAV orthomosaic. The outlines act as a constraint to the building boundary but most of all they help in filtering process of buildings and non-buildings features. In the same way UAVs can be used in places where there are no cadastral maps. Many Boundary detection on building and farm lands have been done by many methods, for example, canny detectors or CNN and remains very successful. A report on 2D outlines have been done by (Lahamy, 2008), but that is a research topic all by itself (could not be done here). Therefore, this research proposes to manually delineate 2D building outlines just to demonstrate the proposed methodology.

4.1.3. Contributions of this paper to the proposed methodology:

1. To which extent the UAVs data can give better 3D buildings
2. To introduce the use of oblique images which can give facades to give the exact building extent

4.2. Methodology workflow

This section explains the workflow of the activities done to achieve the 3D buildings. **Figure 4.1** explains the workflow implementation. After the UAV dense point clouds generation, an orthorecfied mosaic is generated from the UAV point clouds and not the ALS point clouds.

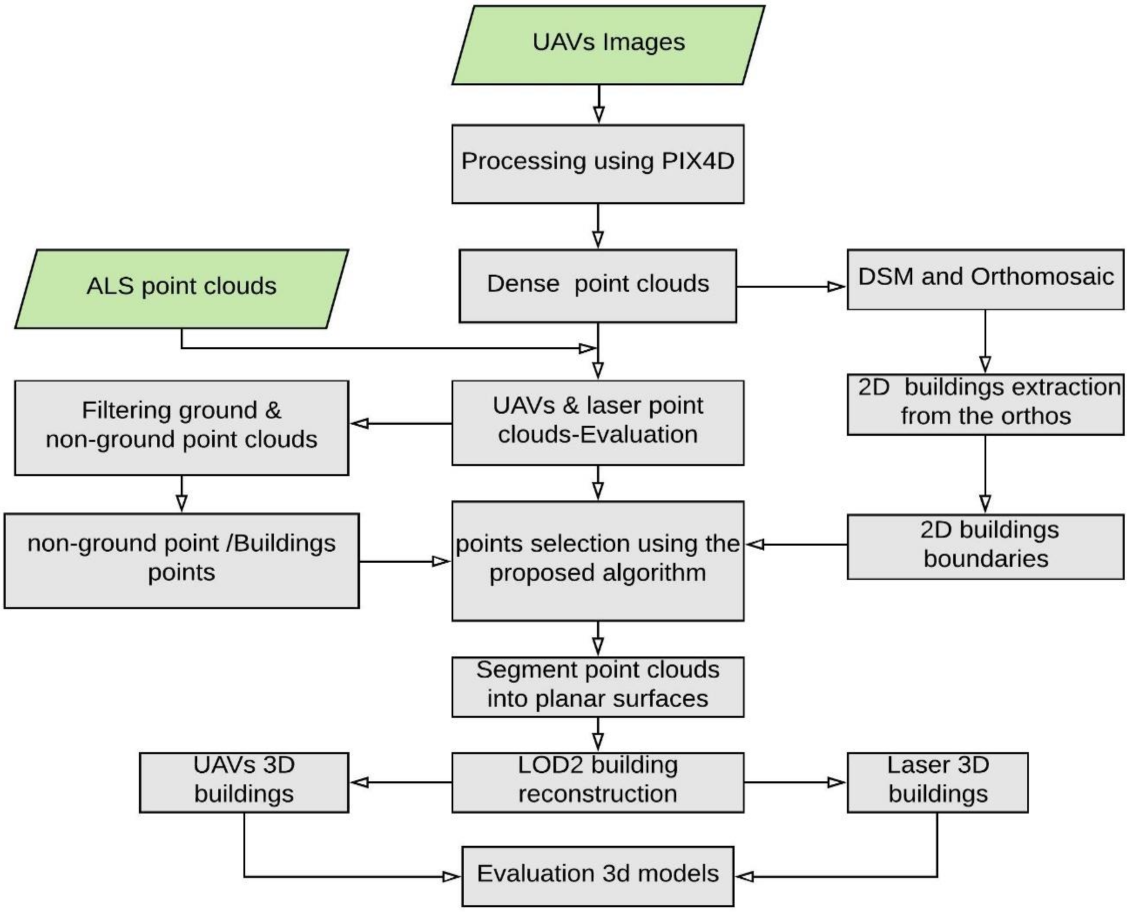


Figure 4-1: The overview of the methodology adopted to reconstruction the 3D buildings from UAV point clouds

4.3. UAV images and Extraction of dense point clouds

This section explains the methodology to achieve objective 1: To evaluate the UAV point clouds as an alternative automatic 3D building modelling as compared to the ALS and the question of if the 3D building models from UAV point clouds are cost effective and accurate enough to replace the lidar point clouds.
Here the three UAV images datasets were processed (Nunspeet, L'Aquila and City Hall Dortmund) in Pix4Dmapper. Pix4Dmapper uses computer vision in finding common points between images. Each unique point found in an image is a keypoint, two similar keypoints are matched keypoints if found in different images. A 3D point is generated by each group of matched keypoints. Hence the more overlap between a stereo pair, the more keypoint and the more keypoints the more accurately the computation of the 3D points by triangulation (Pix4Dmapper, 2019b). A quality report is produced to show the number of the matched images, RMS in GCPs and many other image matchings.

To obtain point clouds from the datasets, images were loaded in Pix4Dmapper and in the case of Nunspeet images, 10 GCPs were read on the images manually. In the Pix4Dmapper there are three processing steps (Pix4Dmapper, 2019)

Dataset one processing:

1. Initial Processing: In the initial processing stage, the software uses the images and the GCPs to identify specific feature in the images as key points. It does keypoint matching by finding all the images with similar keypoints and matching them, it also calibrates the internal and the external parameters of the camera used together with geolocation of the model. Automatic tie points are generated at this step. For Nunspeet images, using the 10 GCPs, a bundle block adjustment was done on the UAV images to improve on 3D position and orientation of the camera (exterior orientation parameters) and identify the XYZ location of each point in the images. The automatic tie points are used as the input to the next processing step of point cloud densification and more tie points are created from the automatic tie points resulting in a dense point cloud.

2. Point Cloud and Mesh: It allow for the setting of the point clouds densification by defining the image scale at which additional 3D points are computed. As mentioned in section 4.3, the computation of the 3D points is by triangulation. The point density was processed in three different scale:

- 1 (Original image size) is the original image scale, meaning a point for every pixel. More points are computed than half image scale
- 1/2 (Half image size, Default) is the recommended image scale in Pix4D, meaning in every 4 pixels we get a 3D point. More points are computed than quarter image scale.
- 1/4 (Quarter image size) is quarter image scale, meaning in every 16 pixels there is a point. Less points are computed than the 1 and ½ image scales.

3. DSM, Orthomosaic and Index: This stage allows for DSM generation and a true Orthomosaic generation since the DSM is used to orthorectify. An optimization technique is used to equalize radiometric differences among images.

Dataset two processing: For this dataset, 0.5 image scale (Default) for the point clouds processing and the processes went as for dataset one.

Dataset three Processing: Two different image scale were tested, 312 images with 0.5 image scale and 110 images with 0.25 image scale were test by manually skipping one images in every sub consequent image thus getting a reduced forwardlap and sidelap.

4.3.1. Comparing the ALS and the UAV point clouds densities

This was done by clipping all the three UAV point scales including the ALS point clouds (Nunspeet point clouds only) to an equal area in ArcGIS software. Create LAS Dataset tool was used to do the statistical analysis of the point spacing of each input dataset. Point spacing is very different from point density, point spacing can be defined as the linear distance between individual points and point density as pnts/m^2. From point spacing, point density can be calculate as 1/ (point spacing)^2. A statistical UAV point clouds was also analysed on maximum and minimum Z.

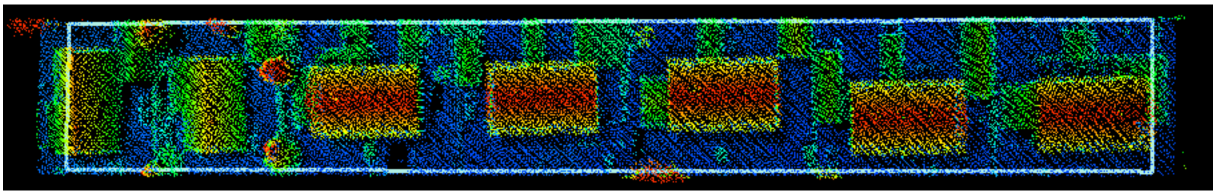


Figure 4-2: The clipped area to assess the point density of both datasets

4.4. UAV points clouds accuracy assessment

This section explains the methodology to achieve objective 2: To evaluate the potentialities of accuracy and completeness of 3D building modelling from UAV point clouds and to see to what extent UAV dense point clouds can reconstruct a better 3D building model as compared to lidar point clouds

4.4.1. Structure from motion (SfM) accuracy report check

The Pix4Dmapper gives a quality report on the accuracy of the point clouds generated after the initial processing stage. In the initial processing stage, the software uses the images and the GCPs to identify specific feature in the images as key points. A quality report is produced which can be assessed to determine the quality of the model which generated the points. The GCPs are assessed for the RMS error.

4.4.2. Comparing the ALS and the UAV point clouds positional accuracy

To compare the UAV positional accuracy, the two datasets were displayed in CloudCompare for visual interpretation of the two-point clouds. The UAV point clouds were displayed in RGB and the ALS point clouds were displayed in height colour code. The positional accuracy was assessed visually by looking at the position of the building in UAV and the position of the ALS buildings as well. This makes it possible to check whether the Lidar point cloud and the photogrammetric point clouds cover the same space.

4.4.3. Internal Accuracy assessment by fitting a plane

ALS point clouds is assumed to be more accurate and was used to assess the accuracy of the UAV point clouds since it was not possible to do a ground truthing which is the best external accuracy assessment for any survey data. Internal accuracy assessment was done by fitting a plane and comparing the distance from the fitted plane and the UAV point clouds, same for the ALS point clouds. To give the noise to the fitted plane in CloudCompare, the algorithm does a least square best fit of a set of 3D points by applying principal component analysis (PCA) (Pearson, 1901). Other two softwares (PyCharm and RStudio) were also compared to see the noise residual. The two-point clouds were displayed, and more than four random areas were clipped from same area, same roof. The sample were taken from different buildings roofs of different colours starting with grey1, red1, grey2, red2, Red3, etc and the number of images which the building roof appeared on were also considered (Grey1=10-images, Grey2= 21-imges, Red1= 16-images, Red2=13-images), see **(figure 4.3).** More buildings were sampled assessed in CloudCompare only (Not included in the samples below).

Figure 4-3 Clipped UAV and ALS point clouds bildings; 1st in the row: Grey1; 2nd: Red1; 3rd: Grey2; 4th: Red2; all were taken from buildings roofs.

4.4.4. External accuracy assessment

For external accuracy assessment, the two datasets were loaded and compared for cloud-cloud distances (C2C) in CloudCompare. A threshold of 20cm maximum pixel value was set to be the maximum distance between the two-point clouds, this was decided to limit the search distance for it takes time if points are further apart. Normally there are two main types of distance compare in CloudCompare: The distances between two-point clouds (cloud-cloud distances) also known as C2C and distances between a point cloud and a mesh (cloud-mesh distances). The C2C normally computes the distance of each point of the compared to the nearest point in the reference points thus the nearest point being on the nearest side. CloudCompare applies the iterative closest point(ICP) algorithms which estimates the closest point between the reference and the compared as the correspondence points by implementing the nearest neighbours and Euclidean distances(Ahmad Fuad, Yusoff, Ismail, & Majid, 2018).

4.4.5. Accuracy assessment by running a profile

Remondino et al, (2014) evaluated the profile of the lidar and UAV datasets since it reveals the matching resolution, potential errors and accuracy. In this research, the two datasets were displayed in global mapper and a profile was run through cutting across the same area. This was to check the discrepancy of the UAV point clouds to the ALS points clouds in the horizontal and vertical position especially on the building since other features like the trees had changed over the time difference in points capture.

4.5. 2D buildings edge extraction from the orthomosaic

The proposed algorithm used 3D point clouds and a 2D cadastral maps. In this research, a manual digitizing in was done to extract the building 2D outlines from the orthomosaic using ArcGIS software. The buildings were extracted manually at the the edge of each image building information. About 35 main houses in the common area of the two datasets were extracted. The 2D outlines was done to act as a contraint to the extent of the 3D buildings and as the base for projecting walls of the buildings and not for the roof generation.

4.6. Filtering of the point clouds

As mentioned earlier, 3D building reconstruction is affected by missing point clouds information, noise, shadows and trees among others. UAV images with trees cannot generate point clouds under those areas, only trees points will be captured, and this inters the reconstruction since the planar segmentation will mistake the trees as building's roof segments giving spikes as a result in the final 3D buildings. Again, trees in the UAV images brings about a missing segment for the missing information since the trees creates shadows which inters image matching during point clouds generation. Generally, filtering apart from classifications and noise reduction, in 3D building reconstruction it can be advised to reduce the size of the point clouds pre to 3D building reconstruction. Three types of filtering were done in the Nunspeet point clouds.

4.6.1. Classification

This was done in Pix4Dmapper after point clouds generation for UAV images. The pix4Dmapper uses unsupervised machine learning to train algorithms for classification. The algorithm uses both colour information and geometry and a trained model is applied which predicts the label of each point then assign it to one of the five classes (High vegetation, buildings, human made objects, roads and ground) (Becker, Häni, Rosinskaya, d'Angelo, & Strecha, 2017). For this data, trees were removed from the classes and the data exported. Tall trees which covers the roof **(figure 4-4)** is a problematic to 3D modelling. The filtering of the ground and non-ground in the ALS cloud points was done on the Lidar360 software. This filtering works on Progressive TIN Densification algorithm by (Axelsson, 2000).

Figure 4-4 Showing trees covering the buildings roofs which needs to be filtered.

4.6.2. Normalized the DSM:

The normalized digital surface model (nDSM) is the difference of digital surface model (DSM) and the generated digital terrain model (DTM), it is computed to represent the object local heights which is the building heights in this research. After classification into ground and non-ground in LiDAR360 software, the point clouds were removed the outliers, generated a DEM of the terrain and finally normalized the point clouds by the generated DEM of the terrain. This was done to get the real height of the buildings excluding the height from the DTM.

4.6.3. Noise Filtering

This was done after classification since the UAV point clouds generation software does the classification automatically and this noise filtering was only to clean the points. One problems of the point clouds are the noise/outliers. Noise is any unwanted detail that makes part of the building reconstruction points, an example can be grass on the roof or other litters which if not removed, may give a wrong geometry due to errors in surface reconstruction. Noise/ outliers may be caused by the taking sensor, matching ambiguities in the case of images, etc. The Nunspeet point clouds were processed for noise filtering in CloudCompare. In CloudCompare, the noise filter algorithm was used to remove the chimneys as unwanted outliers since the algorithm considers the underlying plane and not the distance to the neighboring points, it uses **least square distance** for best plane fit. It does so by fitting a plane around each point and then removes the points which are too far from the fitted plane. Some chimneys were longer than 1m, a radius of 2m was considered and a relative error of 2m.

4.6.4. Clipped to the building polygons

The clipping to the building polygons helps in distinguishing the buildings from other features like ground and vegetation and helps in classification process. This also avoids the overloading of the computer due to many millions of points and removes some of the outliers.

4.7. Defining the real extent of the buildings

This section explains the methodology to achieve objective 3: To integrate UAV point clouds, images information and facades to accurately define the real extent of the buildings and the question if facades generated from UAV point clouds improve the geometry of the 3D building. Buildings are captured from aerial nadir view, and when tracing buildings in 2D or 3D, the aerial view is used to outline the boundary. In most cases, what is normally defined as the roof edge when cadastral data is used in 2D or 3D building reconstruction, does not reflect the real extent of the building especially where there is a roof hang or gutters. Real extent is defined by the facades/walls of the building and oblique images are needed to capture the facades for the real extent that represent the real location of the building on the ground. To achieve this objective, L'Aquila datasets with oblique images were tested:

Extent of wall extraction with Nunspeet images (Nadir)

The Nunspeet UAV images and the ALS data were nadir. The walls captured were only on the aerial perspective and the whole building were never captured for both the UAV images and the ALS data. **Figure 4-5** below shows the walls captured for both Nunspeet point clouds. It can be seen that the UAV images captured the East side wall and half of the South walls and dense points were generated **(figure4-5 Top Left)**, the ALS point were caputured on the east side but very sparse points than the nadir points, the south seems no points and if any they are very few **(figure 4-5 Top Right)**. Looking at the West -North side of the UAV point clouds, it can be seen the UAV images captured little on the west and non on the North wall points **(figure 4-5 Lower Left).** For the ALS, sparse points were captured on the west and half wall points on the North **(figure 4-5 Lower Right).**

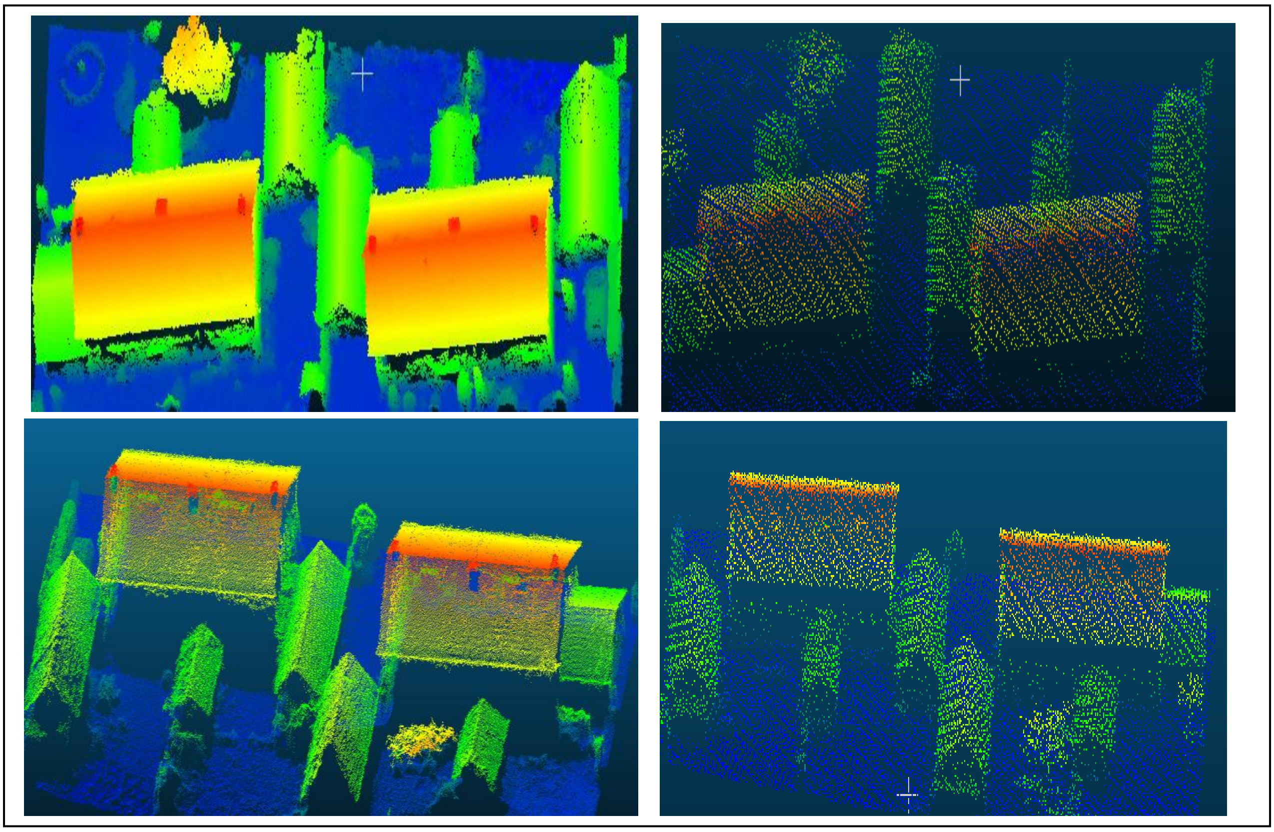


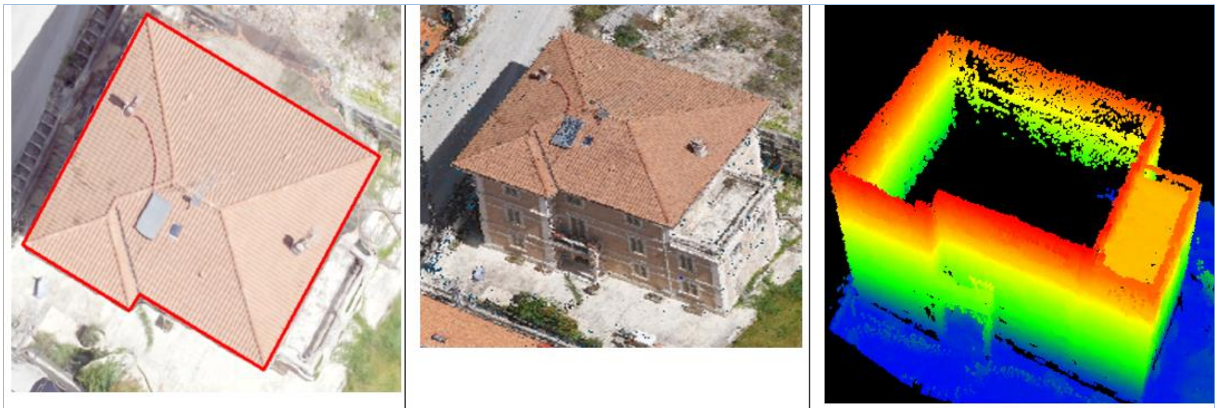
Figure 4-5 UAV and ALS captured walls; Upper left: UAV East-South side; Upper Right: ALS East-South side; Lower Left: UAV West-North side; Lower Right: ALS West-North side

CONLUSION: The UAV nadir images and ALS data does not capture all the walls of a building but only the sides with an aerial perspective thus oblique images are required to complete the walls with point clouds.

L'Aquila images in Italy and City Hall Dortmund (nadir + Oblique)

To realize objective 3, L'Aquila images in Italy were used which had captured the images from all the five views (nadir, oblique North, oblique East, oblique South, and oblique west).

The figure.4.6 below, through (a- c) explains the stages analysed to demonstrate the objective. UAV images processing was done, point clouds and an orthomosaic was created from the images, a building with an iron roof and part of a concrete roof was used to extract image information of the building, image-(a). The point clouds of the building were clipped to a certain Z range (Z range is 691-705m) at a height from the ground (0m-700m) and this left the facades only without the roof, image (c), an outline of the facades edge was done and together displayed with the image information outline.



a):Image information outline on orthomosaic	b): UAV point clouds showing facades capture	c): UAV facades height colour code points

Figure 4-6 (a): Image roof edge information; b)The building point clouds showint the roof and the captured facades

4.8. Planar segmentation

This section explains the methodology to achieve objective 4: To assess an algorithm that can automatically detect whether roof segments are complete and the question of best algorithm to reconstruct a correct and true to reality 3D building model that meets the purpose of many application. assumption is that individual buildings can be reconstructed from a composition of detected planar faces.

Segmentation is very important in the detection of the roof outlines and for the reconstruction approach of the buildings and a set of planar faces can properly model individual buildings. Segmentation is meant to cluster point clouds with similar characteristics into homogenous regions and variety of algorithms is available for segmentation of point clouds. Not all point on the roof or facades represent height information of the building, some points might belong to trees canopy hanging on the roof or for the chimney and dormers instead of the roof. Due to large number of points on the roof, planar roof faces can be detected automatically. In this research the proposed methodology proposes segmentation algorithm by (Oude Elberink & Vosselman, 2009).

To detect these planar points, the Hough transform was extended. They used surface growing algorithm that starts with detecting seeds in Hough 3D space, followed by a least square plane fitting through the point in the seed. Nearby point clouds are added to the growing surface if points are near that plane. The planes were evaluated for missing segments due to occlusion, incomplete segments due to laser sampling at the edges of the building causing also under-segmentation which is a segment belonging to more than one object, over-segmentation which can be caused by the parameter settings depending on the density of the points thus more dense points can lead to recovering more surfaces within the point clouds.

To make sure of connected components and selection of the correct points, segmentation of the points was done and several parameter setting to the algorithm were done for any optimal segmentation to be arrived at. To do the segmentation, the setting of the following parameters was different for the two datasets:

Seedradius is the seed neighbourhood radius (1-2m), **growradius** is the growing search radius (1m), **maxdistancegrow** (0.2-0.3) is the maximum distance of the point to surface, and **minsegsize** (10-30) is the minimum segment to be kept and can vary depending on the point density. There is also **keep-roof**, with parameter settings it keeps roof segments from a certain slope and unclassified those at steeper slope filtering out the walls and even others vertical components formed like trees. Keep roof also has a filtering step where it keeps majority of flat points which is tuned with the flatness parameter.

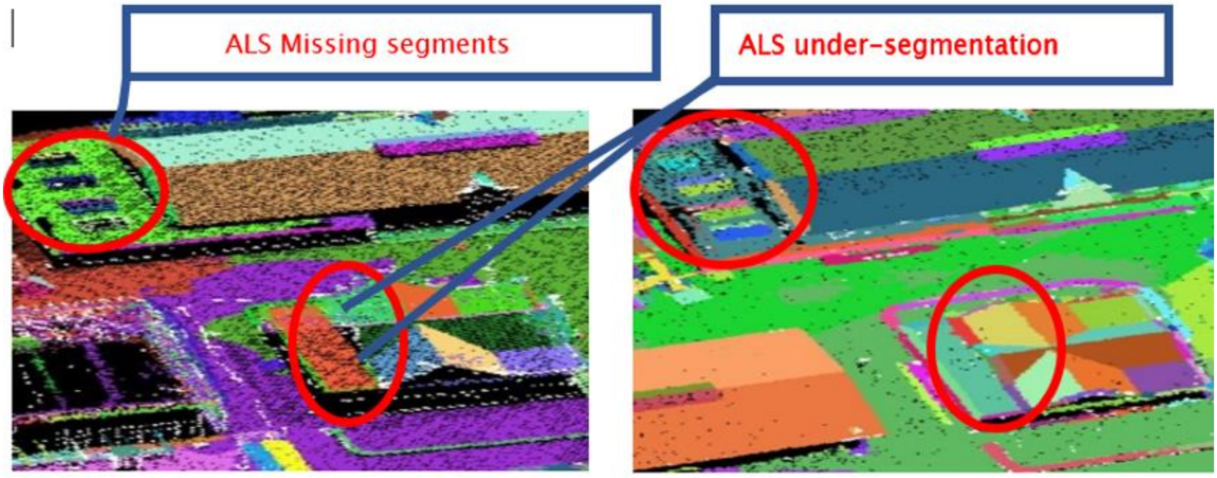


Figure 4-7 Left: showing some missing segments and under-segmentation in ALS (Red circles); Right: showing same areas in UAVs with complete segments and right segmentation

Errors: Errors in segmentation is finding many roof faces within a single segment or few roof faces than the actual building roof segments and this is what is defined as over/under-segmentation which can affect the final building reconstruction. According to Elberink & Vosselman, (2009), lines connecting two roof faces and height jump are part of a topological relationship between two neighbouring segments and if there is segmentation errors, we cannot detect the roof faces and height jump. If within a segment an intersection line or a heihgt jump is detected, the segment is split into two parts and more splitting if more height jump and intersection lines within roof segments are found.

4.9. Automatic Facades/walls detection from UAV point clouds

To automatically detect the facades from the UAV point clouds, it must be assumed that walls are 90 degrees vertically and this had to be considered in the setting of the segmentation parameters in the proposed methodology. Wall just like the roof faces are searched by segmentation and detected automatically. If the keep-roof filters the walls then a keep-walls can filter the roof and keep the walls. The proposed algorithm cannot run if the point clouds are more than 7,000,000 points. Due to large number of points on the roof and on the walls, planar faces on the walls will be challenge on long and tall buildings which captures millions of points. The proposed algorithm runs only with a maximum of 7 million points. An alternative on the walls may be to reduce the image scale during point cloud generation to 0.25 (quarter) or 0.125(an eigth) and have less dense point clouds. To reduce on point density this was tested on the City Hall Dortmund dataset **(section 4.3).**

4.10. LOD2 building reconstruction

For a complete and correct building reconstruction depends on the segmentation results. 3D building modelling is based on the planar faces detected and so the segmentation process as to give a true representation of the roof faces of the building. For the modelling of the building, segmentation is used as an input together with the point clouds and the buildings information outlines (cadastral map) (B. Xiong et al., 2016). His algorithm was applied to reconstruct the 3D buildings and how it works was explained in **section 4.1.1.** The walls are assumed to be vertical, and the roof are a composition of planar faces. The roof takes the shape of the segmented planar faces, in case of errors like over and under-segmentations, the buildings are incorrectly reconstructed because the roof shape is dependent on the segmentation results.

The Loss of information in ALS is a common problem for example, the point density or occlusion on the different levels of the roof furniture, and this affects the extraction of the buildings by ignoring the local details like dormers and other roof elements.

4.11. 3D building evaluation

Accuracy evaluation and the quality of 3D buildings has been done in literature. Dorninger & Pfeifer, (2008) presented an orthogonal vertical difference between the 3D model and the reference point clouds. (Oude Elberink, 2010; Ostrowski, Pilarska, Charyton, & Bakuła, 2018) used similar approach as Dorninger and pfeifer. Elberink & Vosselman, (2011) however, argued that the perpendicular distance from the point clouds to the 3D models might be misleading since most points are close to the models. In this research, many accuracy assessments have been done on the UAV point clouds and the reference ALS data in the previous chapters. The evaluation was done to see if the algorithm automatically detected and reconstructed a correct and true to reality 3D building model from UAV point clouds that meets the purpose of many application as compared to ALS point clouds. It was done to assess on the completeness of the roof furnitures, which dataset automatically detected a complete roof, and whether the 2D buildings outlines enhanced the edge boundaries of the UAV point clouds building boundaries. The algorithm has a tool to evaluate the quality of the created buildings by giving a quality report document which tell the percentage of the well-constructed buildings. To evaluate the completeness and the quality of the 3D buildings from the UAV point clouds, the ALS data was used as a reference and since the 3D building extent was same for both datasets, the horizontal extent was the same and the only difference was the vertical distance. In this research, two quality checks were done, a visual interpretation and an overlay of the segmentation contours since an optimal segmentation defines the final structure.

5. RESULTS AND DISCUSSION

5.1. UAV images and Extraction of dense point clouds

5.1.1. Results of UAV images of dataset one (Nunspeet)

After the processing of the UAV images, the following results were achieved in **figure 5-1.** The 1 scale (Original image size) looks so dense, the points are too close together followed by the 0.5image scale (Half image scale), and the 0.25 image scale (Quarte image size) showing the least points spacing. It is clear that the setting of the image size produces different point densities which is determined by the number of matched pixels. It also be seen that the point clouds from the aerial view are uniformly distributed, and no clusters or holes in between the point clouds. All the 312 images were aligned and matched in the pre-processing report. Much of these results will be explained in later chapter since it's the main data for 3D building reconstruction especially the 0.5 image scale.

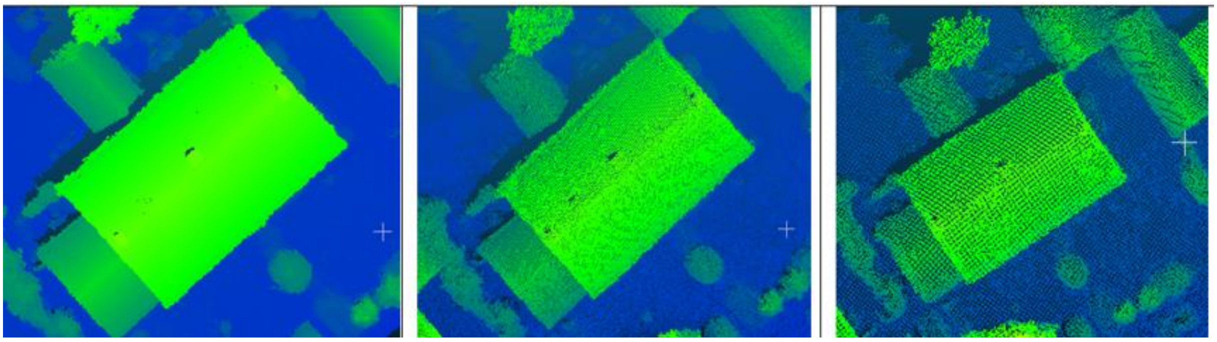


Figure 5-1 Different point densities from the UAV image scale settings in Pix4Dmapper; Left: Original image size; Centre: 0.5 (Hals image size- default); Right: 0.52 (Quarter image size)

5.1.2. Results of L'Aquila and City Hall Dortmund image processing

L'Aquila images in Italy and City Hall Dortmund were oblique plus nadir images. To realize objective 3, L'Aquila images in Italy were used which had captured the images from all the five sides of a building (nadir, oblique North, oblique East, oblique South, and oblique west). Each set of images were processed separately (starting with East images) and most of the images were not matched and could not be aligned in every set of images. After the merge of all the five projects, there was a mis-match of the walls and the roofs due to imperfect geolocation of the images and lack of GCPs on the ground **(figure 5-2 -Left),** it can be seen that there were 3 roof layers and two walls (**Red circles).** In between tall buildings it can be seen some missing point which were not generated for the walls **(figure 5-2 -Centre), t**his might have been caused by some occlusion and some images might have failed to be aligned and finding a match.

To Align the mis-aligned walls and roofs of all the projects, each project was brought into CloudCompare and each was aligned to the other by the plugins" Align two cloud points by picking 4 common points", this is a registration by applying a transformation matrix. The results were achieved **(figure 5-2-Right**), it can be seen the projects were aligned to one roof and one wall. The merged project had over 99 million points and almost all the walls were captured except the areas in between the close buildings and ones next to tree canopies and other types of occlusions. The walls were more than 1m thickness **(a challenge on where is the exact location of the wall plane).** It can be noted that the manual tie points did not work for a perfect alignment.

The City Hall building gave over 7million points for 312 images **(figure5-3- first row-left),** and the 110 images gave comparable good point clouds, **(figure5-3 first row centre)**. Reducing the number of images overlap still gives acceptable results with reduces noise. **Figure 5-3 first row- right image**, shows the cross-section of the wall point clouds. The challenge of many images is the noise, as it can be seen **in figure 5-3 last row**, the cross-sectional wall point clouds thickness is 82cm which is a challenge to the plane fitting.

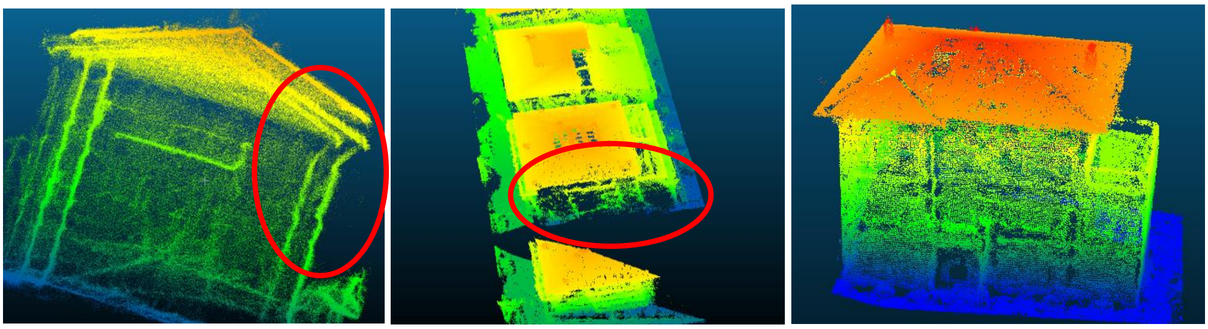


Figure 5-2 L'Aquila processed point clouds; left: mis-matched walls and roofs before registration; Centre: Missing points in between the walls; Right: Aligned point clouds- Thick walls and undefined windows.

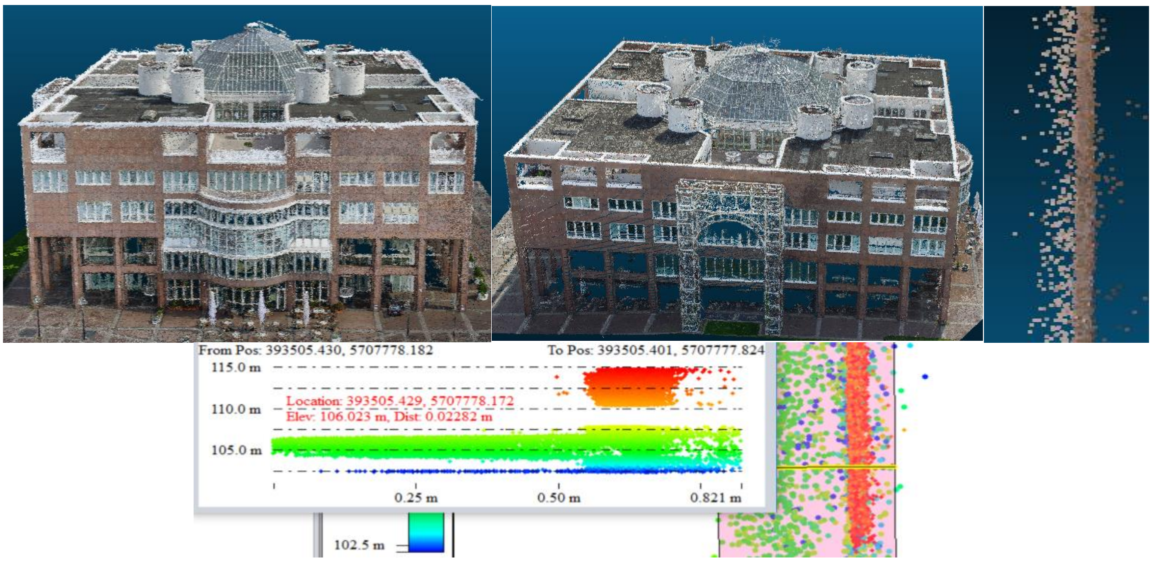


Figure 5-3 First row; Right 320 images point clouds; Centre:110 images point clouds; Right: cross-sectional wall points; Lower row: The cross-sectional wall profile.

Findings:

L'Aquila point clouds

- It was not easy to align the L'Aquila projects, but it is doable
- Even after alignment, there was a lot of noise to the points, the walls were very thick, doors and windows were not clearly defined, a lot of filtering the noise had to be done
- The points distribution was not uniform, a lot of holes in the data were clear, some areas with more cluster kind of distribution of points.

City Hall Dortmund point clouds

- The City Hall Dortmund was well aligned by looking at the windows and the doors and the images aligned perfectly.
- All facades were captured smoothly
- The 312 images were nosier than the 110images with reduces overlap

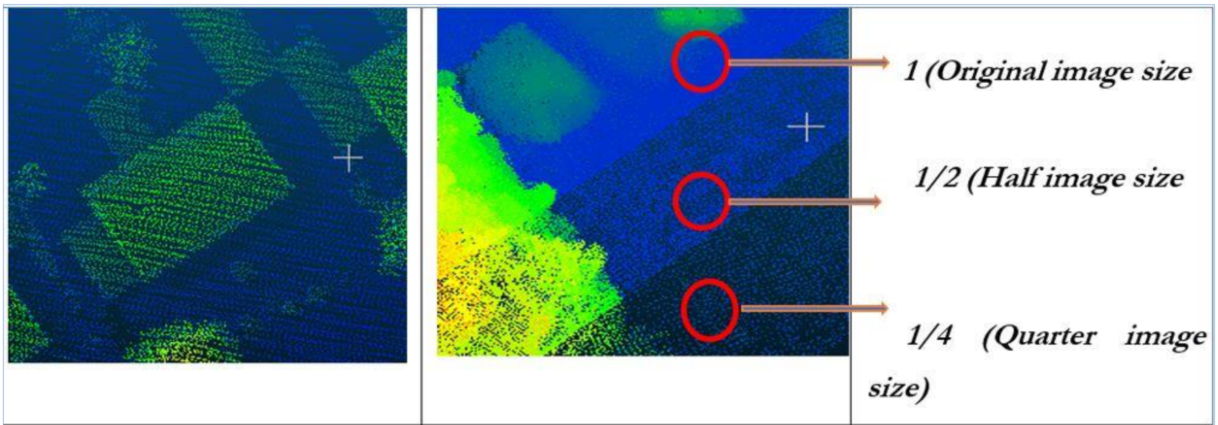
Conclusion: It is possible to capture all the facades from the 360 degrees view of a building

5.1.3. Results of Comparing UAV and ALS point clouds density

Remondino et al., (2014) argues that on aerial acquisition, laser gives 1-25 points/square metre dense point clouds, while an aerial photogrammetry with a typical GSD of 10cm can produce a dense point clouds of 100 points/square metre. The point clouds were compared with respect to point spacing, point density, number of points in the clipped area and positional precision as well as minimum and maximum Z. The photogrammetric point cloud has a higher density of points/m^2 while this value is less for Lidar.This is evident by looking at (Figure.5-4), the bright the color the denser the points. Looking closer at the statistics (Table.5.1), the spacing of the photogrammetric points is less than that of Lidar thus denser point clouds. In the same table it can be seen that the photogrammetric point count is greater than Lidar points count within the same clipped area size. A good explanation to this is that UAV images were of good ground sampling distance (GSD) and the matching algorithm is capable of giving points in every pixel assuming no occlusion, shadows, non-reflectance surfaces among others in the case of image size scale.

The Z values shows how well the two-point clouds align vertically **(Table.5.1).** The UAV 0.5 image scale and the ALS are compared, the UAV had min Z as 7.987m above sea level and max Z as 23.419m above sea level. The difference of the minimum Z values is 0.453m and the Maximum is 1.61m between the two-point clouds. This can be explained by the fact that UAV point clouds on the minimum Z value is due to the fact that it had more of an oblique view of the ground and might have captured a lower points than the Lidar, and on the maximum Z value the difference is 1.61m , this might have been caused by the difference in time of data capture causing the trees to have grown tall in the UAV dataset than in the ALS data which was taken much earlier. Starting with the image scale, half image scale, quarter image scale and ALS point clouds, the densities can be approximated as: 1520/m^2, 345/ m^2, 78/ m^2, 15/ m^2, respectively by using the point spacing (Table.5.2).

In this research, the 0.5 image scale was chosen to work with for the 3D buildings reconstruction reasons being that the points were ideal after filtering of noise and choice of features wanted on the roofs. The 1 image scale was not to be considered reason being it generated many points which were unnecessary for this research for it had the disadvantage of creating more surfaces during segmentation process which gives incorrect final 3D building, 0.25 image scale after filtering the noise, had the disadvantage of removing all the roof furnitures including the wanted ones like the dormers, thus not included in the research for 3D reconstruction. Most of the point cloud comparison was done on the Nunspeet point clouds because in this data there was a reference data, the ALS data.



(a): ***ALS points*** (b): ***Overlay of the three UAV point densities***

Figure 5-4 Point density visual interpretation of Pix4Dmapper scales to get a clear view of the point density Plus the ALS point density on the left.

Table 5-1 Showing point count, point spacing, maximum and minimum Z of the 4-point clouds.

File	Version	Point Count	Point Spacing	Z Min	Z Max	Statistics
UAV_Image scale.las	1.2	5274128	0.025	7.857	22.997	...
UAV_Half image scale.las	1.2	1230494	0.051	7.987	23.419	...
UAV_Quarte image scale.las	1.2	298540	0.106	8.233	22.655	...
ALS Points.las	1.2	53901	0.256	8.440	21.810	...

Findings:

- The photogrammetric point cloud has a higher density of points/m^2 than Lidar points

5.2. UAVs point clouds accuracy evaluation

5.2.1. Results of UAV triangulation RMS errors

Table 5-2 shows the results of the RMS of the GCPs after triangulation in the initial stage of the processing. According to ASPRS accuracy standards for digital geospatial data ASPRS, (2014), the accuracy standards for aerial triangulation errors can be 3 times the ground sampling distance (GSD) of the images. The 10 GCPs show quite good residuals in XYZ the highest being 1.24cm in X thus the RMS errors are good compared to the GSD of 1.65cm with a mean error of 1cm (Adding the XYZ residuals and dividing by 3). This can be explained by the fact that the images were of good contrast, high resolution, well captured and the GCPs were accurate and read properly on the images and the images aligned perfectly.

Table 5-2: Structure from motion (SfM) RMS accuracy report for GCPs

GCP Name	Accuracy XY/Z [m]	Error X [m]	Error Y [m]	Error Z [m]
MP01 (3D)	0.020/ 0.020	-0.013	0.014	-0.005
MP02 (3D)	0.020/ 0.020	0.009	0.013	0.009
MP03 (3D)	0.020/ 0.020	0.024	0.008	-0.002
MP04 (3D)	0.020/ 0.020	0.016	-0.014	-0.021
MP05 (3D)	0.020/ 0.020	0.003	0.002	0.001
MP06 (3D)	0.020/ 0.020	-0.000	-0.014	0.003
MP07 (3D)	0.020/ 0.020	-0.009	-0.000	-0.001
MP08 (3D)	0.020/ 0.020	-0.013	-0.009	0.006
MP09 (3D)	0.020/ 0.020	-0.015	-0.001	0.008
MP10 (3D)	0.020/ 0.020	0.001	0.002	0.009
Mean [m]		0.000225	-0.000007	0.000774
Sigma [m]		0.012410	0.009653	0.008750
RMS Error [m]		0.012412	0.009653	0.008784

Findings: The photogrammetric point cloud has a low triangulation RMS error for GCPS, and it is lower than the GSD according to ISPRS digital data standards meaning the orientation was good.

5.2.2. Results of comparing the ALS and the UAV point clouds positional accuracy

This was a visual interpretation of the two datasets, it could have been done in an GIS visualization software. By overlaying the two-point clouds with the image building information outlines, it is evident that the two overlays perfectly horizontally **(figure 5-5).** This makes it possible to check whether the Lidar point cloud and the photogrammetric point clouds cover the same space especially around the buildings. The RGB coloured buildings are of the UAV point clouds, the blue points are the ground points for the ALS, the dark green points are the roof points of the lower buildings and green points are the higher roofs points. As can be seen the RGB buildings of the UAV point clouds is a perfect match with the ALS height coloured point (Left).

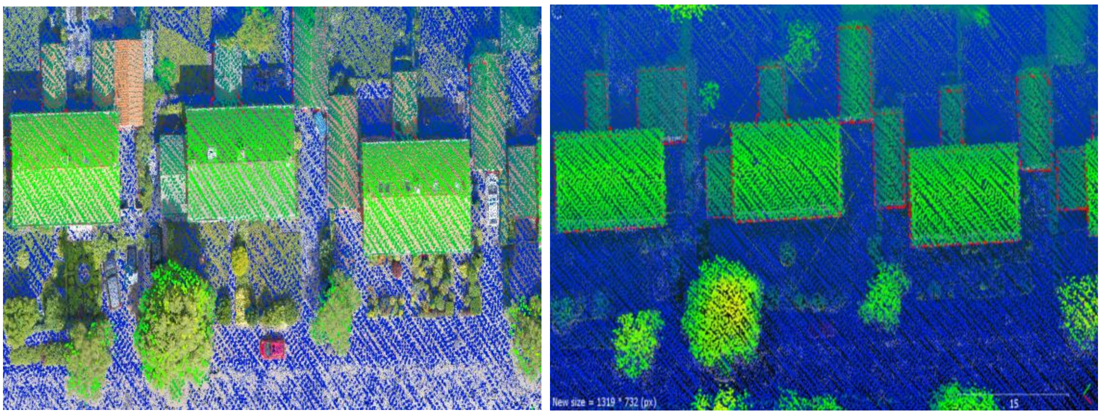


Figure 5-5 Comparison of the positional accuracy of the two datasets; Left image: An overlay of UAV and ALS points; Right image: An enhanced view of the 2D image information from the ortho and the ALS point clouds- quite a match even though acquired from different methods.

Findings: Positional accuracy is acceptable enough looking at how the two datasets fit horizontally, and the ALS points fit exact within the 2D building edge information extracted from the orthomosaic

5.2.3. Results of internal accuracy assessment by fitting a plane

The results of fitting a plane in the UAV point clouds and the ALS data was to assess the amount of noise in the data. More than four random samples were assessed, and the standard deviation was 0.0121m, 0.0117m, 0.024m, 0.011m respectively for the UAV, and 0.030m, 0.078m, 0.018m, 0.018m respectively for the ALS in CloudCompare best plane fit algorithm. The results were so smooth that other two (2) more softwares had to be compared. **Table 5-3** gives a summary of the three (3) softwares used to assess the amount of noise in the two-point clouds, this gave the level of noise from the fitted planes and the points. The difference in the roof's standard deviations for the UAV point clouds can be explained as due to the fact that the images of the UAV data are not uniform throughout the area of coverage and this can vary due to circumstance affecting the images at that point. It can also be argued that the type of the roof colour does not matter here for it is clear the errors are not related to red roof or grey and same can be explained for the ALS point clouds. The big error in the **grey2 roof** can be explained as a result of the roof being not slanted but flat (most likely the roof was not tiles but concrete) and this could have accumulated more materials on the roof like tree leaves and grass and even the roof texture looks homogenous **(section 4.4.3-third image)** making it difficult to have a good matching resulting to noise. Also, grey3 happened to be a flat roof with 0.033m error. The number of images has no contribution to the noise as it can be seen 10 images of grey1 roof has an error of 1.2cm, Grey2 with 22 images-error of 2.4cm (increased), grey3 with 11 images- error of 3.3cm (increased more than the 22 images). The 3 softwares had almost same noise residuals, but CloudCompare was a bit refined with mostly 0.01cm better (a-h images of the residuals and software used. From, left: CloudCompare; Right Upper: RStudio; Right Lower: PyCharm - see **Appendix**;).

Table 5-3 Comparison of the CloudCompare, Python and RStudio in best plane fit errors

Building roof colour	No. of images appeared	UAV -std in CloudCompare (Unit-m)	UAV - std in RStudio (Unit-m)	UAV - std in Python (Unit-m)	ALS points - std in CloudCompare (Unit-m)	ALS points - std in RStudio (Unit-m)	ALS points - std in Python (Unit-m)
Grey1	10	0.0121	0.0144	0.0143	0.030	0.0386	0.0376
Red1	16	0.0117	0.0129	0.0129	0.078	0.088	0.0843
Grey2	20	0.024	0.0253	0.0253	0.0182	0.0193	0.0189
Red2	13	0.0107	0.0103	0.0103	0.018	0.022	0.0209
Red3	41	0.00702					
Grey3	11	0.0334					
Red4	40	0.0166					
Grey4	14	0.0149					

Findings:

- The UAV point clouds had less noise in most cases than the ALS point clouds, meaning for surface reconstruction was good.
- The texture of the roof matters most for the UAV, and flat roof, maybe more noisy

5.2.4. Results of external accuracy assessment by comparing distances

The results show that values higher than 20cm maximum threshold distance were excluded, the mean distance was 0.162m and the standard deviation was 0.046m (**figure 5-6).** The highest coloured areas represent target UAV points far from any reference ALS point. Areas particularly on the ground, top of the buildings and trees, show higher range of colour. Normally, the deviations are an indication of the low quality of UAV point clouds in certain areas or less dense point clouds of the lidar especially on the roof, ground and on the trees. This can be explained that the ALS point clouds did not capture dense points as compared to the UAV, On the trees is due to the fact that the UAV datasets was taken later when there were already a lot of changes on the ground and the trees had grown and for ALS there were no close points. For the chimneys is due to the fact that the ALS points were sparse and none, depending on the size of the chimney and the ALS point spacing, fall on them but they were captured in the UAV. Generally, the red colours can be concluded as due to the less dense ALS point clouds and the change in data capture between the ALS and the UAV images. As the differences are mainly concentrated on the trees and on limited portions of the scene, these results confirm the suitability of the UAV for surface reconstruction.

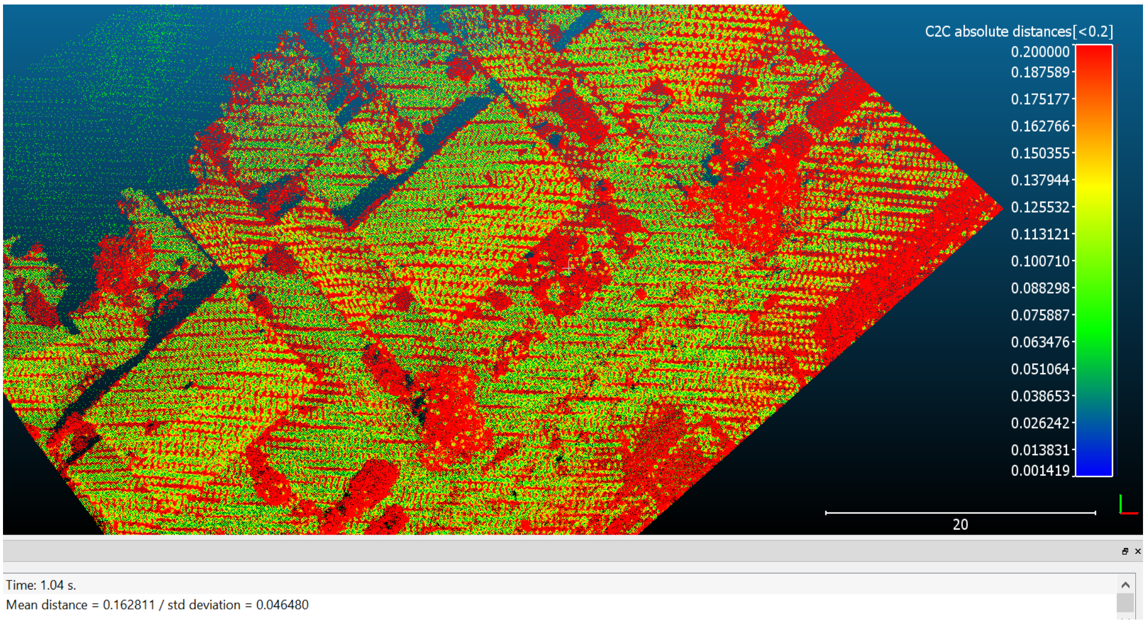


Figure 5-6 The external accuracy assessment of the two datasets

5.2.5. Results of the profile

The positional accuracy of the UAV data seems same with the ALS when looking at the length of the data across the two buildings **(figure 5-7).** The height accuracy is in the same range as looked through the height of the roof and the tallest chimneys which is approximately 16.5m and 17.25m respectively. The UAV points gives a smooth chimney canopy than the ALS points. The point clouds of both data give more less the same profile and a model reconstruction will give same.

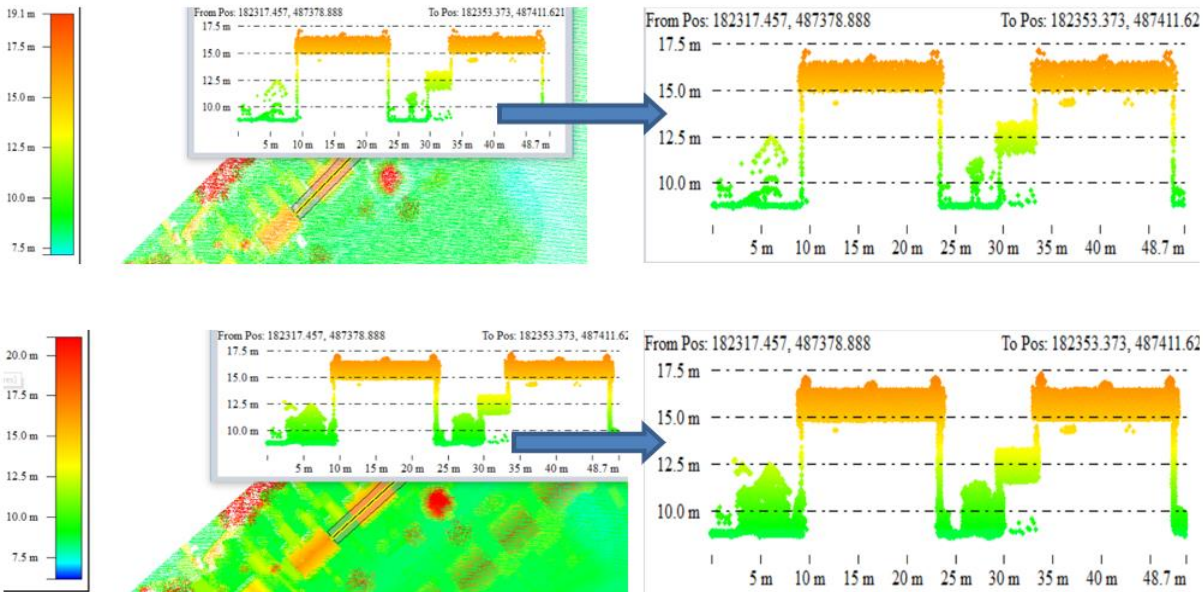


Figure 5-7 Top image: ALS point clouds profile; Bottom image: AUV point clouds profile; Vertically and horizontally both covers same distance by visual interpretation.

5.3. Results of the digitizing buildings from the UAV orthomosaic

Over 35 main houses were digitized manually **(figure 5-8).** Some of the main buildings are attached to small other buildings which were done separately. Shape of the buildings were captured as accurately to the roof edge as possible and only the common area with the ALS were digitized leaving out the UAV new developed area.

Figure 5-8 2D buildings digitized manually from the UAV orthomosaic

Findings: Trees can be an iterance to digitizing as well as the shadows when the image is dark**.**

5.4. Filtering of the point clouds

5.4.1. Results of the classification

Figure 5-9 shows the results of filtering in both UAV and ALS datasets. It can be seen that the ALS point clouds (upper images -a &b) were filtered to ground and non-ground point. The UAV point clouds were filtered through trees up to the buildings only (d-f). As mentioned earlier, the Pix4Dmapper uses machine learning with trained data. Has can be seen by close look, there are misclassification. some buildings, just patches were classified as high vegetation, or as human made objects or even as road surface. This can be explained due to the colour of the building roof or mostly where there were trees canopy casting shadow on the roof there were no points for the UAV data. Not advisable to filter that much, to avoid missing data information from the UAV point clouds, only high vegetation was removed **(figure 5-9- d)**

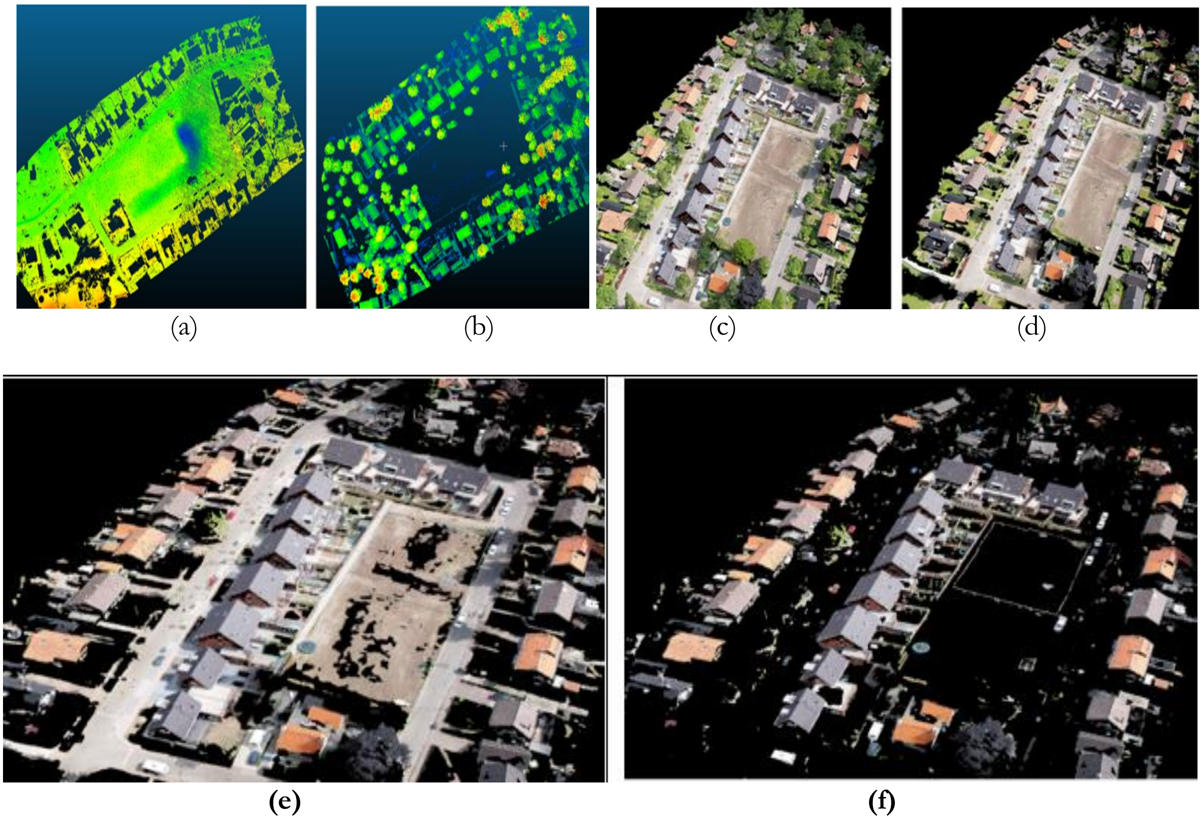


Figure 5-9 Upper ALS images filtered to ground (a) and non-ground (b); c-f: UAV point clouds showing filtering results to remain with only buildings after filtering all the other classes.

5.4.2. Results of the nDSM

Normalizing the UAV and the ALS point clouds makes it possible to get the local height of the buildings which can be determined from 0-level (bottom) to the top-roof. This is the height which the building should be at and not the included DTM height which was over 16m for the same buildings **(figure 5-7)**. The results show that the approximately height of the consecutive three buildings is 7.6m. This is evident by looking at the profile of the two datasets **(figure 5-10).** The profile confirms the same building height for the UAV and ALS, this can be another accuracy assessment for the volume in the final 3D model.

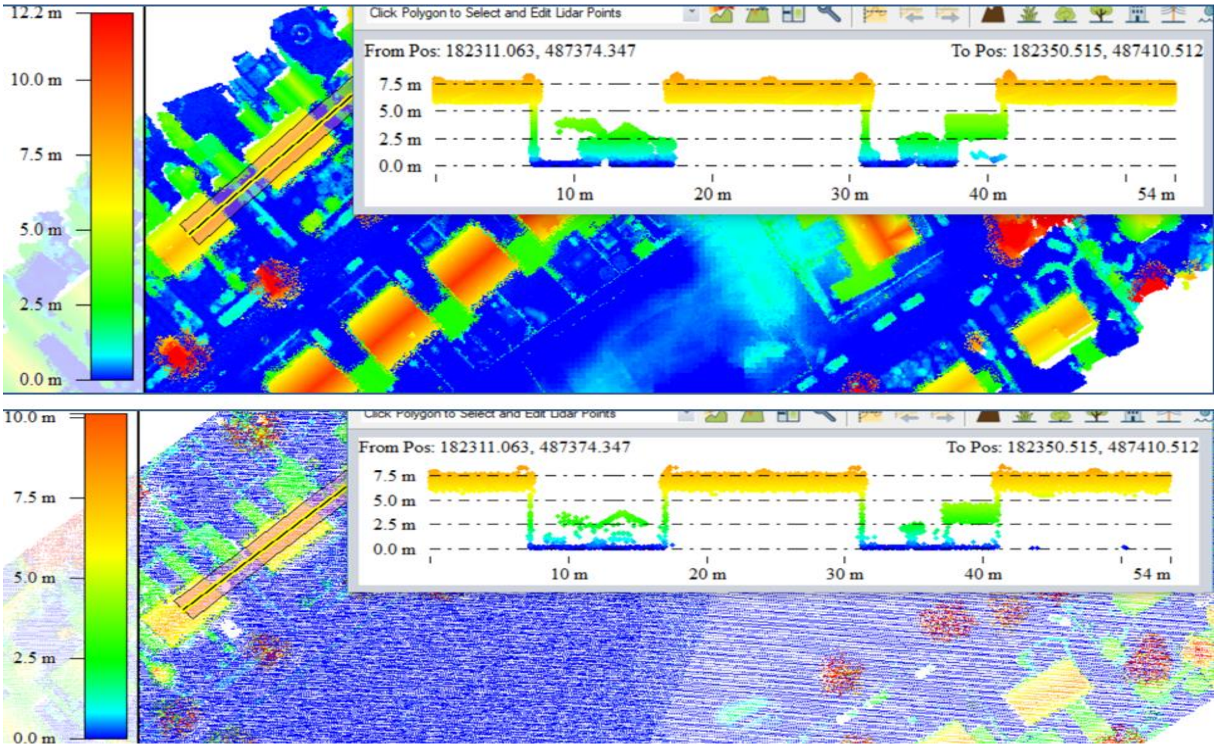


Figure 5-10 Upper image: UAV data profile, lower image: ALS data profile; showing the real height of the buildings

Findings: It is obvious that the UAV fits well with the ALS data and it shows that the UAV point clouds can be as correct and accurate as the ALS point clouds both horizontal and vertical dimensions.

5.4.3. Results of noise filtering

Figure 5-11 shows that the unwanted chimneys and other roof furnitures which brings further segmentation can be removed by noise filtering. The noise filtering is done by the least squares for the best plane fit algorithms, and by close look, it is seen that it reduces the points density and completely trims all the chimney to empty space for both the UAV and the ALS point clouds **Figure 5-11 & 5-12** respectively.

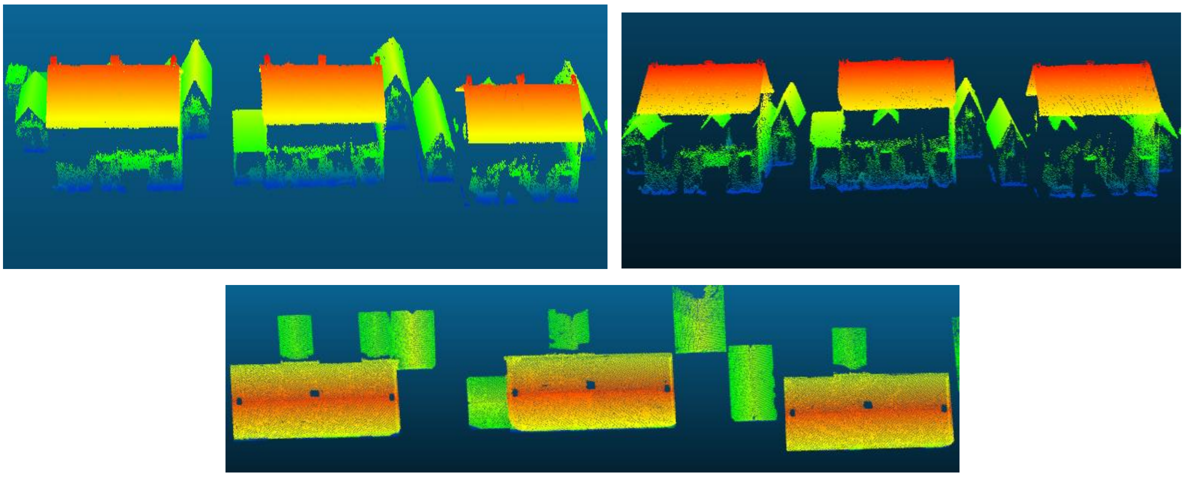


Figure 5-11 Upper Left: Showing results before filtering; Upper Right: Results after filtering; lower image: Showing removed point clouds in the areas around the chimneys

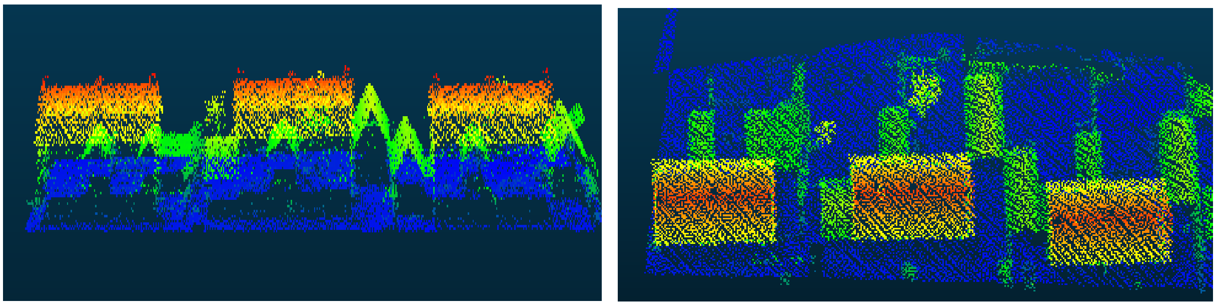


Figure 5-12 ALS point clouds before filtering; Right: ALS point clouds after filtering

5.4.4. Results of Clipping the point clouds to the building polygons

Figure 5-13 shows the clipping of the point clouds to the building polygons which makes it easy also to distinguish the points of the building from other features. This clipping does not remove the tree canopy on top of the building as it can be seen from the results. The **red circles** are the evidence of tree canopy on the ALS building's roof. As for the UAV buildings, most of the trees on the roof were removed by classification filtering in the Pix4D. As it can be seen, some of the buildings in the UAV point clouds seems smaller and missing the roof points after filtering since the building under the trees had no points captured due to occlusion or due to misclassification errors (**figure5-13; Left image- red circles**). The effect was analysed in **section 5.10**.

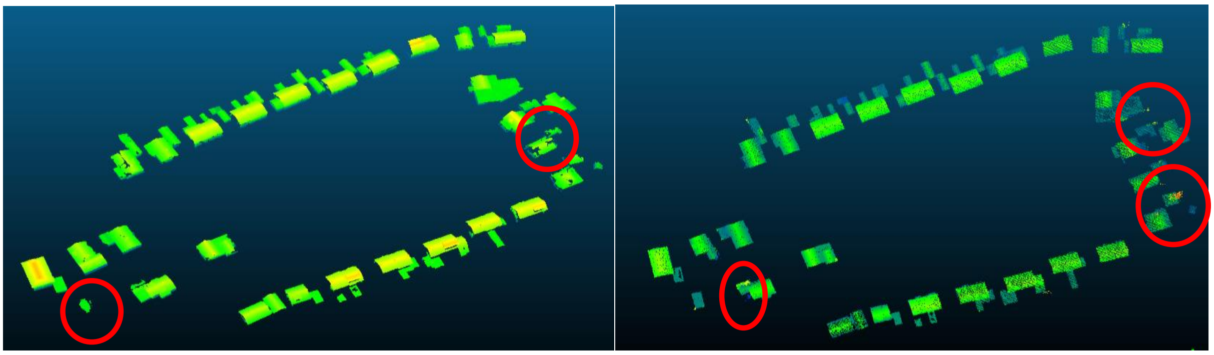


Figure 5-13 Left: UAV point clouds; Right: ALS point clouds

5.5. Results of defining the real extent of the buildings

In this part the work of facades to define the real extent of a 3D building is addressed **(figure 5-14)**. After clipping the buildings to expose the walls, **figure5-14** (a) and displaying it with the orthomosaic **figure5-14** (b), it was evident that the two do not have the same extent. An outline of both facades edges together displayed with the image information outline (c), the red line is for the image building information and the blue line is for the façades edge and the two showed totally different extent. The real extent is defined by the facades/walls of the building and oblique images are needed to capture the facades for the real extent. **Figure 5-14-a)** shows the walls of the building without the roof and the points are coloured by height. **Figure 5-14- b)** shows the walls extent and the building image information extent. It is seen that the extents are not the same for the walls and for the roof. **Figure5-14- c)** shows the outlines of the building image information and the outline of the wall's positional extent.

a) UAV pointss height color code *b) UAV Roof edge and façades extent displayed* *c) Outlines of the roof and the facades- Different extent*

Figure 5-14 The really extent of the building as demonistrated by the facades.

Findings: The tests concludes that the real extent can be achieved by UAV multi-oblique images by capturing the facades. It is seen by clipping the building to a certain height, can exclude the roof and then, manually or by edge filters the façades boundary is extracted. By displaying the facades edge and building image information, the real extent is achieved. Incases where there is no roof hang, the image building information and the facades edge will be bang-on (same extent). For automatic façade detection later - **section 5.7.**

5.6. Results for planar segmentation

After the parameter setting for the two data sets different setting gave different results depending on the point density. The focus was on the segmentation quality of the completeness and correctness of the roof planes using the orthomosaic as a quality check **(figure 5-15).** Looking at the orthomosaic visually concludes how correctly the roof planes has been detected. Chimneys are not considered because during segmentation, small segments not meeting a minimum number of points are removed and this can be done by increasing the minsegsize which removes most of the chimneys, also this was done through noise filtering. By comparing the roof segments and the orthomosaic, the accuracy is expressed by the completeness and the correctness of the segmentation contours. From **figure 5-16 to 5-22**, different parameter settings are represented for both UAV and ALS before noise filtering and there after results after noise filtering are presented **(5.6.3).**

Figure 5-15 UAV Orthomosaic for Possible roofs, dormers and chimneys found by the segmentation search

5.6.1. UAV point clouds segmentation parameter setting

After different parameter settings, **figure 5-16 to 5-18** shows the results of the segmentation. Some settings show over-segmentation, others show under-segmentation or a combination of both. It is obvious that different parameter settings give different segmentation results.

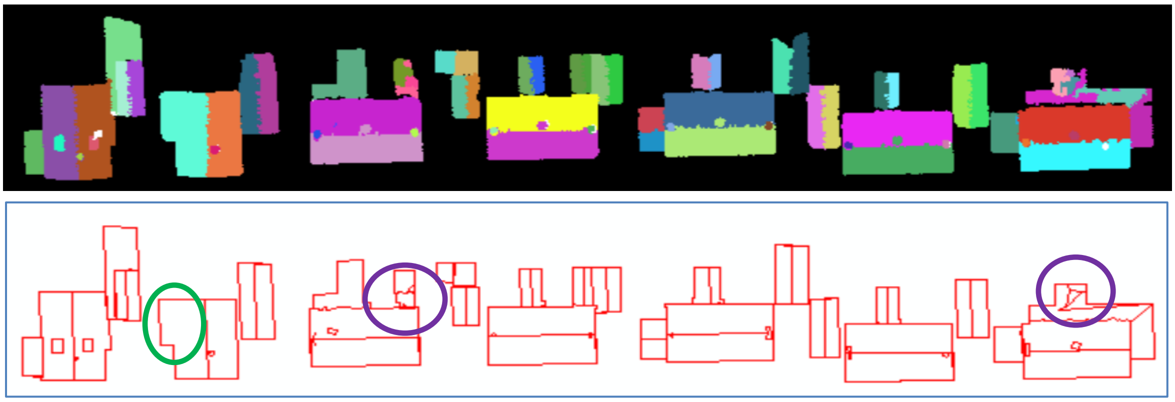


Figure 5-16 UAV; seedradius 1.0 -growradius 1 -maxdistgrow 0.3 –minsegsize 30- Chimneys and dormers are visible, some over-segmentation (green circle) and under-segmentation (purple circles)

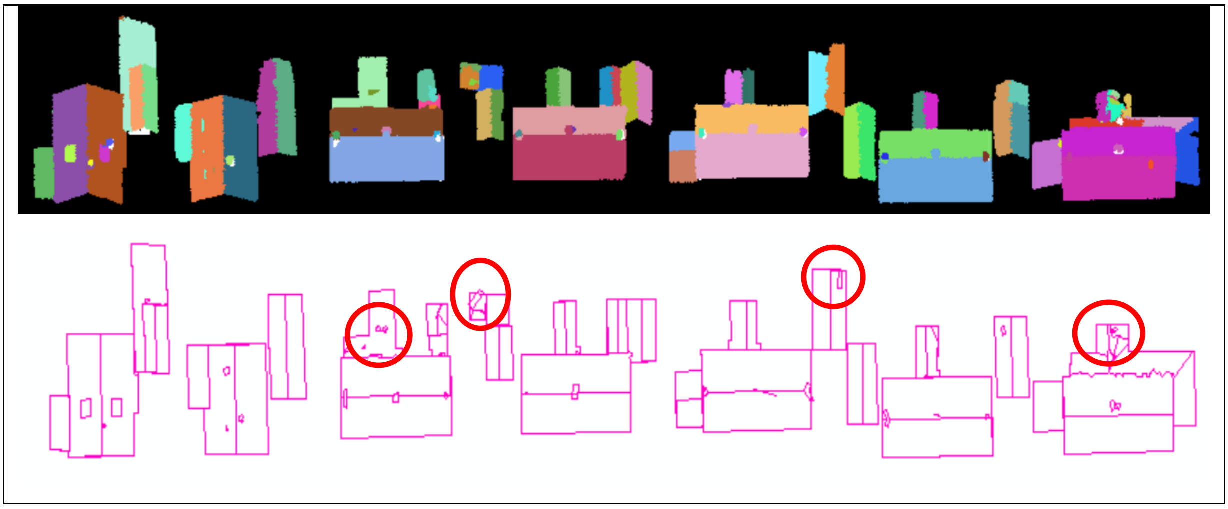


Figure 5-17 UAV; Seedradius 2.0 -growradius 1 -maxdistgrow 0.3 –minsegsize 30; More surfaces seen due to many points within the increased seedradius.

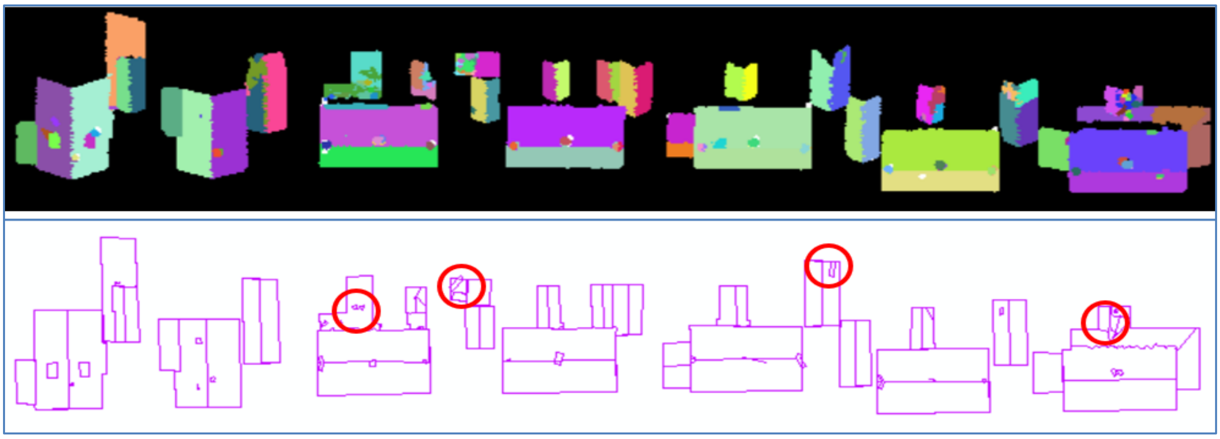


Figure 5-18 UAV; Seedradius 1.0 -growradius 1 -maxdistgrow 0.1 –minsegsize 10; More surfaces are found-Over-segmentation (Red circles)

5.6.2. ALS point clouds segmentation parameter setting

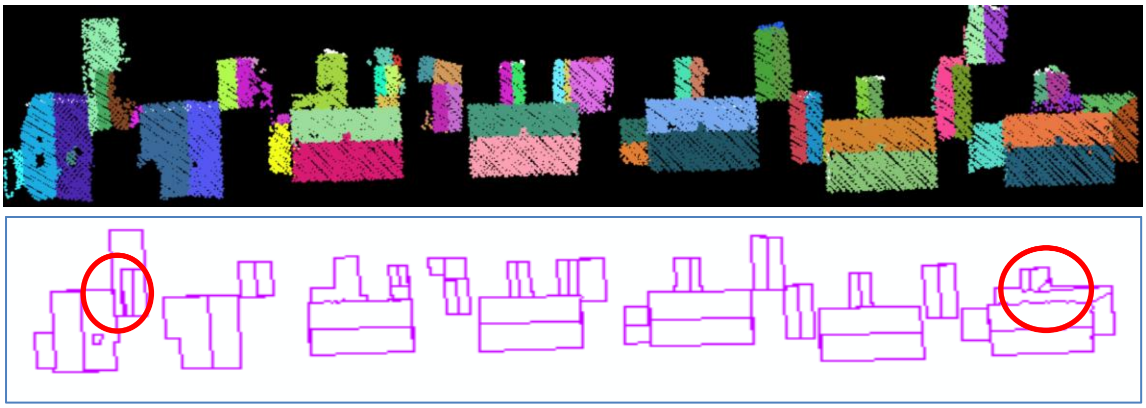


Figure 5-19 ALS; Seedradius 1.0 -growradius 1 -maxdistgrow 0.3 –minsegsize 30; flatness 0.75: Inceasing the maxdist grow to 0.3m, some more surfaces starting to show on the segmentation contours (Red circles)

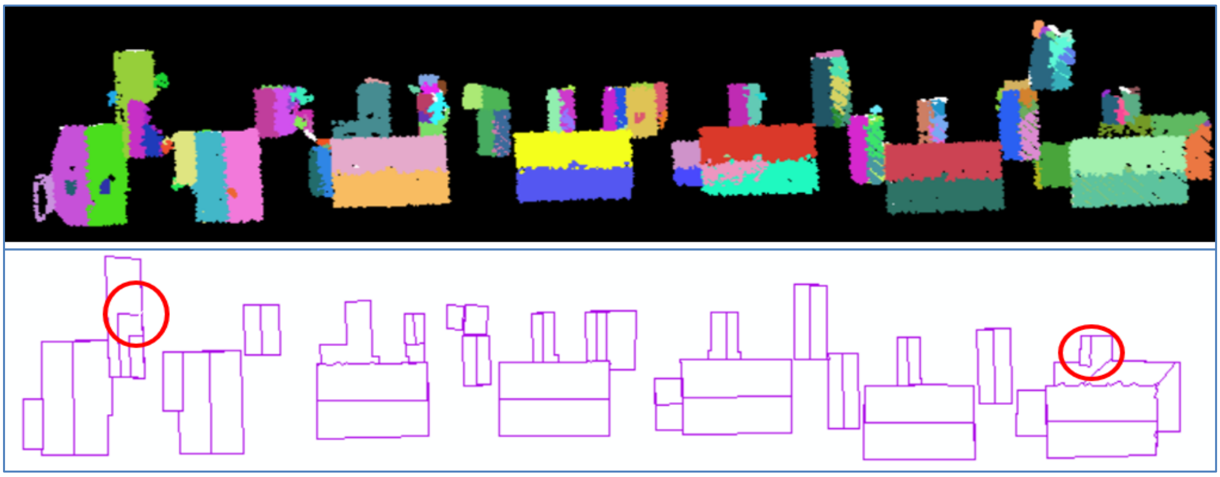


Figure 5-20 ALS; Seedradius 1.0 -growradius 1 -maxdistgrow 0.1 –minsegsize 10; flatness 0.75. With flatness 0.75, trees are filtered but segments are not clean (red circles) -Over-segmentation

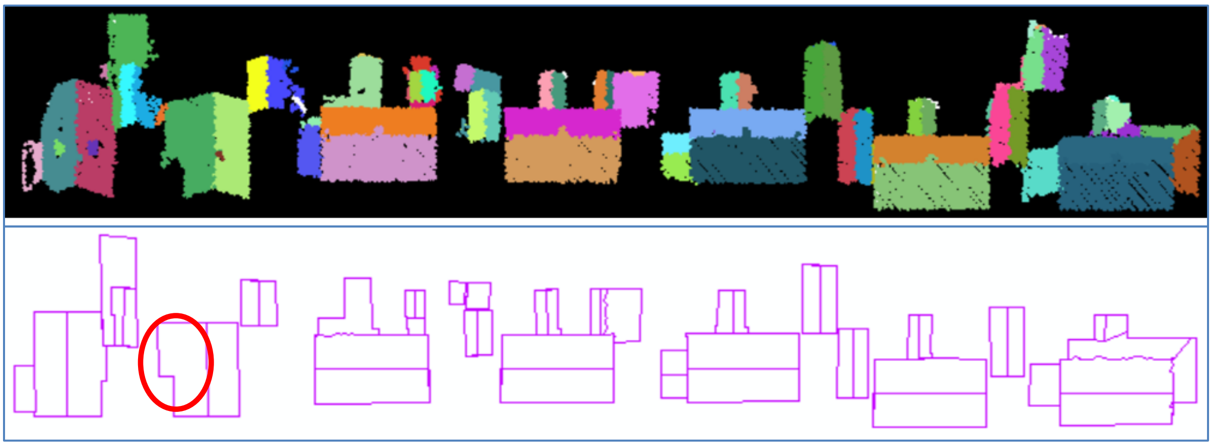


Figure 5-21 ALS; seedradius 1.0 -growradius 1 -maxdistgrow 0.3 –minsegsize 10; By reducing the minsegsize to 10 and maintaining maxdistgrow 0.3m, there is under-segmentation of some roofs (Red circles) - optimal segmentation

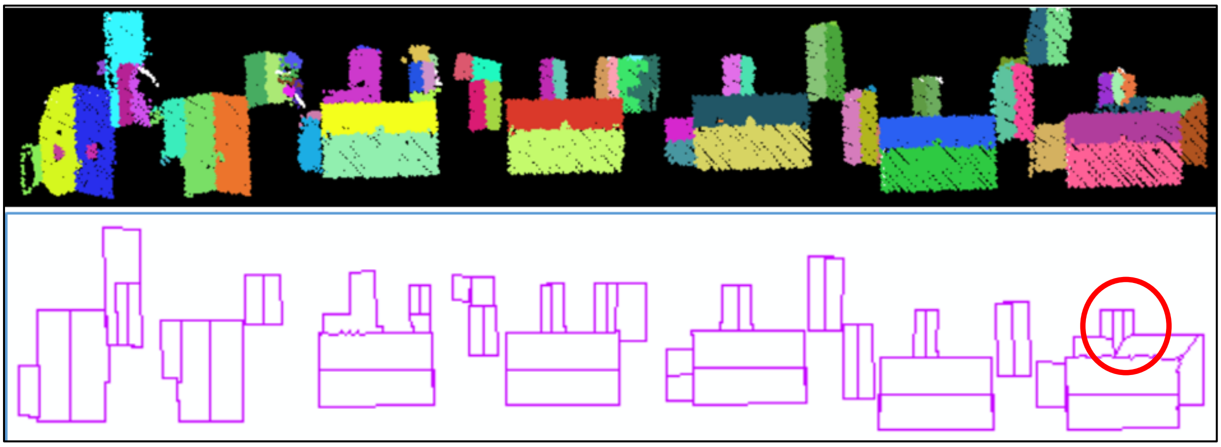
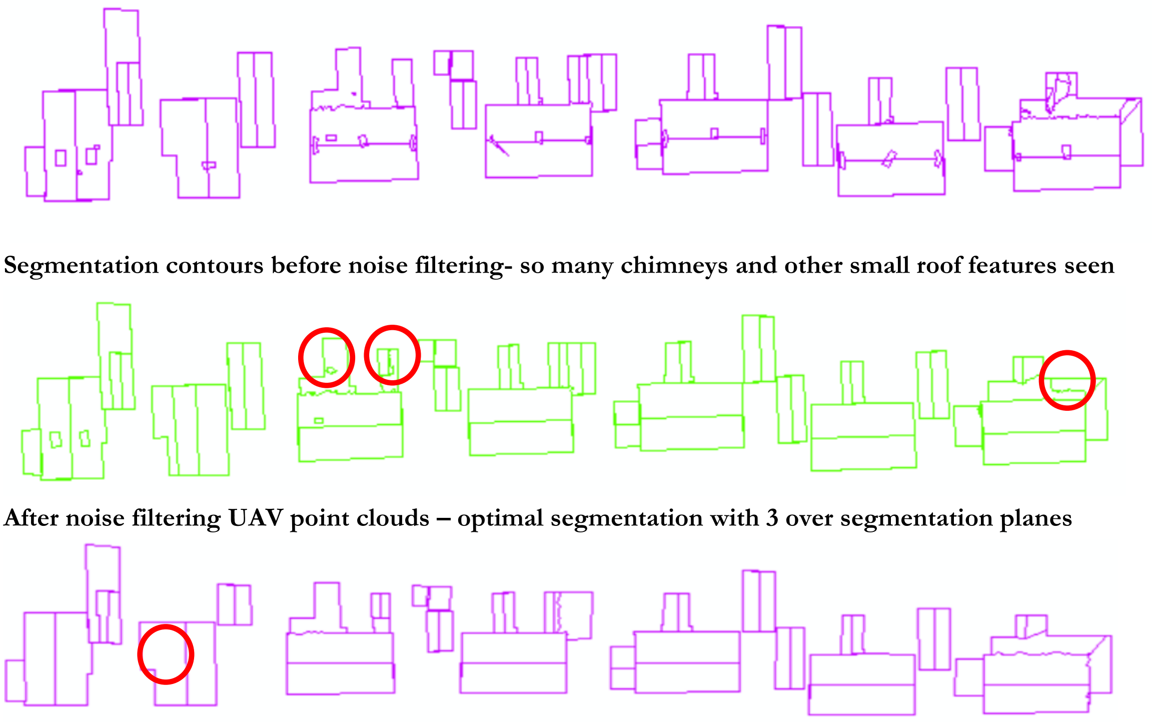


Figure 5-22 ALS; Seedradius 1.0 -growradius 1 -maxdistgrow 0.2 –minsegsize 10; flatness 0.75. give optimal segmentation.

5.6.3. Further comparison of the optimal segmentation contours after noise filtering

Figure 5-23 shows the results of optimal segmentation and Table 5-4 shows the comparison of the two datasets in terms of planar segmentation errors. In the table 5-4 results for this part of the datasets there are about 13 main buildings with 51 roof faces. The optimal segmentation shows that the over and under-segmentation errors for this section alone and give 98% accurately planar segments for the ALS and 96% for the UAV. Same pattern is expected in the subsequent parts of the same data.



Segmentation contours before noise filtering- so many chimneys and other small roof features seen

After noise filtering UAV point clouds – optimal segmentation with 3 over segmentation planes

ALS optimal segmentation contours with one under-segmentation

Figure 5-23 Optimal segmentation comparison of UAV and ALS segmentation results

Table 5-4 Optimal segmentation comparison of UAV and ALS segmentation results.

		Total	ALS point clouds	UAV point clouds
1	Roof faces	51	100%	100%
2	Dormers	2	0%	100%
3	Over-segmentation		None = 0%	3/51=3.8%
4	Under-segmentation		1/51= 1.9%	None = 0%
	Optimal Roof planar segmentation		50/51=98%	48/51 = 94%

Findings: The parameter setting depends on points density for the optimal segmentation. For the less dense ALS point clouds, the minimum segment is less (10 points) than the minimum segement in UAV point clouds which is more dense(30 points) in this research. The setting might change for another area within the same data or a setting might work for a number of buildings in one area but one building within those fails, and in another settings the segmentation is good (**figure 5-21 and 5.-22**-for the two ALS optimal settings). **Figure 5-24**, shows the segmentation paremeter setting for UAV data, this time minsegment size remains the same but the seedradius increased to 2m. The UAV contours (left image)shows the parameter setting of: Seedradius 2.0 -growradius 1 -maxdistgrow 0.3 –minsegsize 30; flatness 0.75. and Right image shows the parameter setting of: Seedradius 1.0 -growradius 1 -maxdistgrow 0.3 –minsegsize 30; flatness 0.75. The left gives the optimal segmentation results for this area.

Figure 5-24 Comparison of parameter setting in same dataset; shows different parameter setting is required in different section of same data.

5.7. UAV automatic façade detection

Results of automatic facades/walls detection from UAV point clouds was not in these results. **figure 5.25 upper row** shows the segmentation was done and detected only the roof contours. The problematic of the automatic detection of this algorithm is the point density, if only one building has more than 7Mil. points then it will not be possible to detect the planar faces.

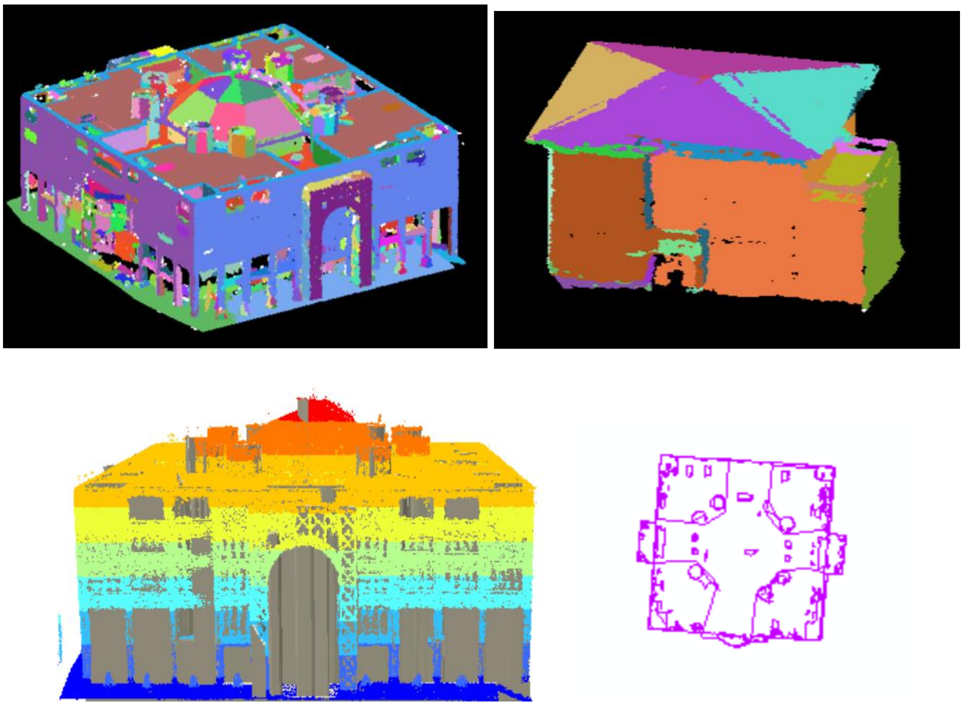


Figure 5-25 Upper row: showing segmentation can take place but only the roof contours are automatically detected; Lower left: Reconstructed building; Lower Right: Shoeing only the roof contours.

Findings: The automatic façade detection is possible and just like the roof segmentation parameter setting, for facades it can be done by snapping the contours to a parallel plane to the wall, but the problematic point is the detection of a big buildings like city hall Dortmund and others big buildings with points more than 7Million points.

5.8. Results of 3D building reconstruction

3D buildings reconstruction using dense point clouds from UAV remains the most important objective in this research. The modelling process was carried out for two datasets by using the same planar faces segmentation algorithm with different parameter settings. The study examined the modelling correctness of the buildings with reference to the orthomosaic by visual interpretation of the buildings in comparison to the ALS 3D buildings **(figure 5-26 Left)** and UAV buildings **figure 5-26 Right.** For the modelling accuracy, buildings models were one by one chosen from each side (ALS and UAV) and a visual interpretation done on them. Both were compared to the expected shape from the orthomosaic. Just as discussed in the segmentation, that there is different parameter setting within one dataset, and within it one or two buildings can be incorrectly segmented, same will results is the reconstruction stage. **Figure 5 -27** explains the reconstruction results of one parameter setting different from the another and how a manual editing was done.

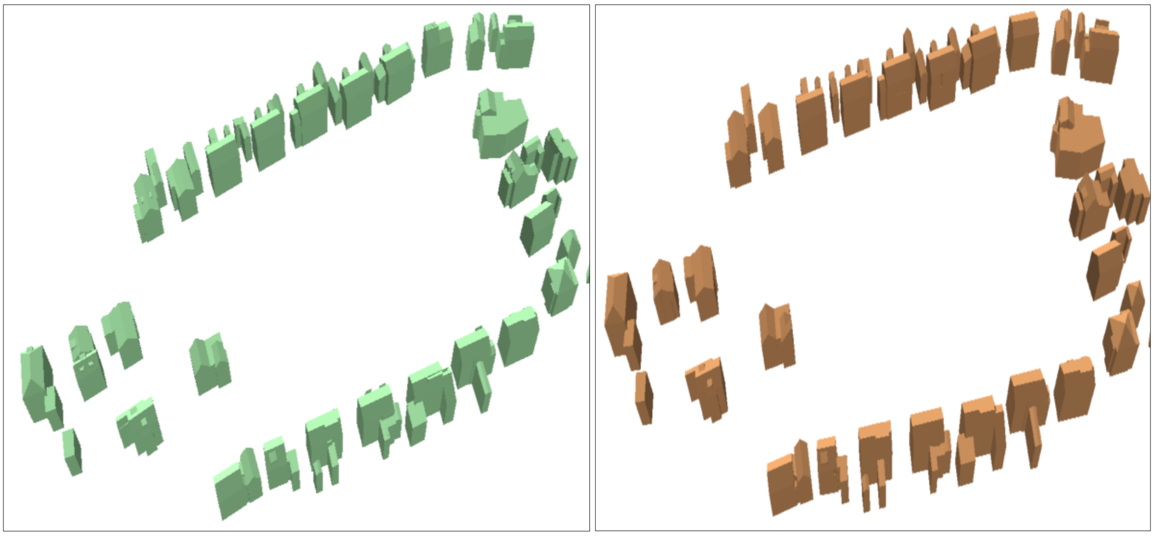


Figure 5-26 Left: Final UAV 3D buildings; Right: Final ALS 3D buildings

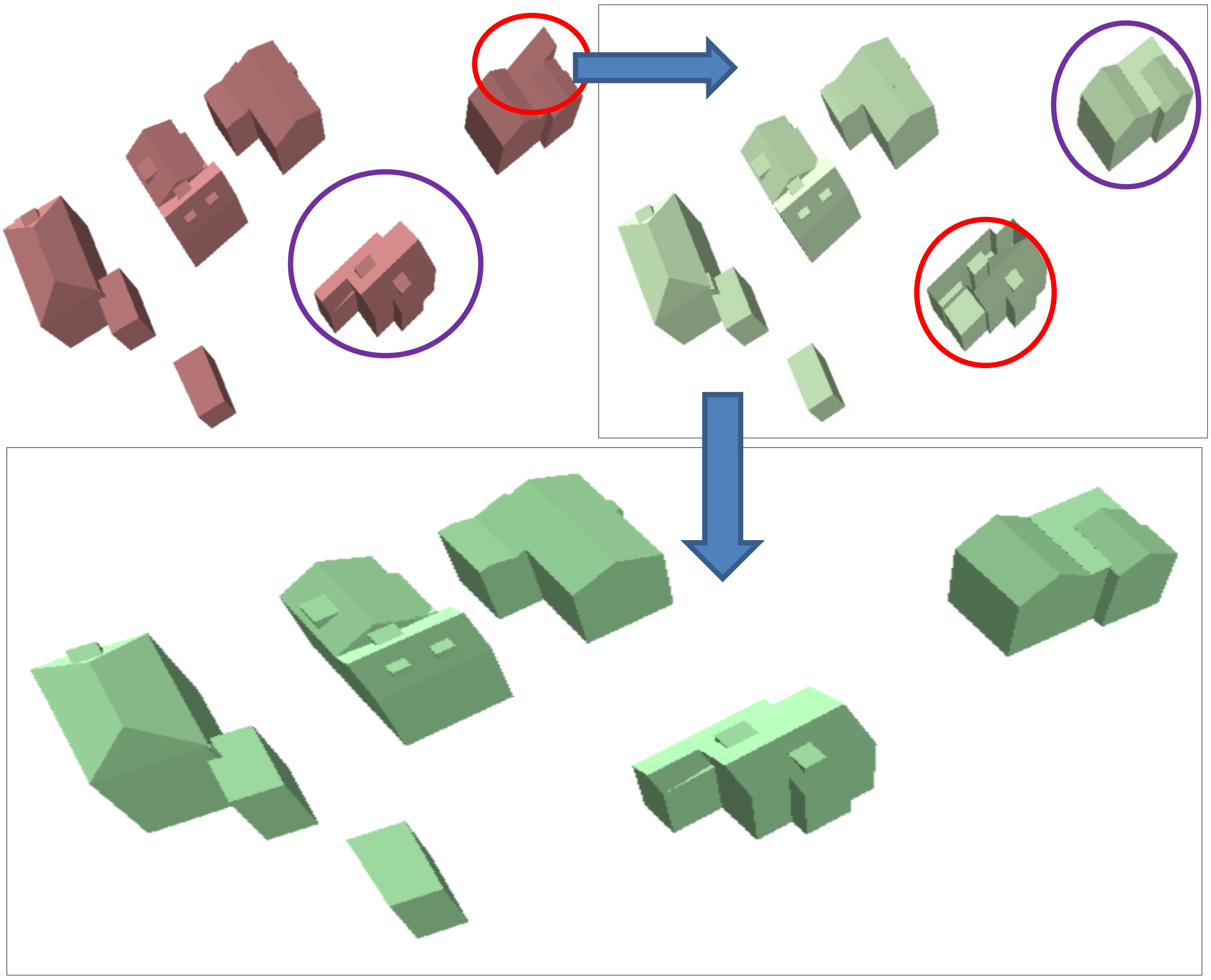


Figure 5-27 A demonstration on how different parameter settings works differently in one dataset; Top left:One good(Purple circle) and one bad (red circle) modelled buildings; Top Right: One good and one bad modeled buildings from different parameter settings; Lower image: A complete set of complete buildings after replacing either of the bad reconstructed Building by delete and cut paste.

Findings:

- Some UAV buildings have more furniture on the roof like dormers and the chimney.
- Due to dense point clouds of the UAV, some buildings might have more partitioning than is the reality on the ground as a result of more surfaces recovery from the data during segmentation.
- Results of the ALS 3D buildings reconstruction was as a result of one parameter setting giving only one bad reconstructed model but for AUV point clouds, two different parameter settings had to be done in different area of the same dataset to get correct buildings and a third parameter setting done on the bad reconstructed buildings.

Conclusion: It can be concluded that there can more than one parameter setting within one dataset for both UAV and ALS for it is not easy to get all the buildings correct within the entire area with only one parameter setting. For the wrongly reconstructed buildings one can get another parameter setting option and complete and correct buildings can be achieved through manual delete, cut and paste.

5.9. UAVs Images and 3D building reconstruction

The fifth object is to evaluate the improvement of 3D buildings from a combination of multi-view and oblique UAV images as compared to lidar point clouds and how can this be translated to the flight path planning. Although the photogrammetric point cloud is considered less accurate, the advances in technology has made it possible to create highly accurate maps from drones for a wide range of applications. The findings in this research has shown that, UAVs can be the siutable platform for improvement of 3D buildings from a combination of multi-view and oblique UAV images. ALS captures roofs and does not capture wall except which are only visible from an aerial perspective view, so UAVs can combine the advantage of both TLS and ALS for it can capture walls and roofs. This was evaluated by comparing the UAVs oblique images to the ALS point clouds to see which parts of the buildings are visible from the images and from the ALS data.

The UAVs systems can provide very high resolution data for it can be manipulated to fly lower with high overlaps, the higher the flying height, the bigger the GSD and the poor the resolution of the images acquired. The GNSS/INS onboard provide for automated navigation and photogrammetric images orientation, GPS and IMU are used for direct-georeferencing but ground control points (GCPs) are needed to refine the accuracy of the models, this has been used in **dataset 1.** The challenges for ALS is wall occlusions and point density but this can be improved by taking of nadir and oblique multi-view UAVs images in areas that can not be accessed by ALS or narrow street between buildings improving on the 3D building reconstruction. ALS leaves holes/gaps with no points between the ground and roofs and the UAVs imrove on the buildings by capturing the facades giving a true LOD2 building represention of the point clouds, this has been demonistrated.

To capture the facades and and take care of occlussions, oblique images with bigger overlaps are needed to take care of occluded areas in narrow streets between buildings and other features. Dataset 2 has demonstrated the use of many overlapping nadir and oblique images. Remondino et al., (2017) gives the 80% forward overlaps and and same for side overlaps. They go further to state that this comes with extra cost because bigger overlaps, many images and many images many flight lines. But, do we really need all these big ovelaps in all situations?, like in this research only the point clouds used for 3D reconstruction were the roof point clouds. The case of City Hall Dortmund has been presented with 312 images and 110 images, and the results are comparably good even with less image overlaps. The one building city Hall with 312 images at 360 degrees view could still be managened with normal traditional photogrammetric overlap of 65-60% forwardlap and 25-30% sidelap this could avoid unneccessary point clouds.

Conclusions:

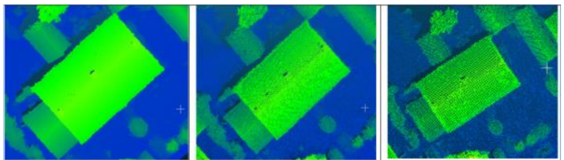
- For the 3D building reconstruction with the interest of the roof points, no need for the oblique multiple overlaps of 80% by 80%, the nadir images with traditional overlaps is sufficient for the roof points
- The 0.5 image scale is good enough for the roof features and optimal segmentation without over/ under segmentations depending on the parameter settings
- With a minimum of 50 pnts/m2, most of the planar surfaces are reconstructed comfortaly, but for smaller features than dormers on the roof, a more denser point clouds than 80/m² is needed

5.10. Addressed 3D building reconstruction problems in this research

Had stated earlier in the chapters, vegetation, missing data information and point density have been mentioned has the major problems in 3D building modelling. Some of these problems have been solved by the proposed algorithm and the data processing methods used in this research.

a) Point density

It has been seen that the UAV point clouds are denser more than the ALS point clouds. This can recover more roof furniture.



(a): *1 (Original image size*	(b): *1/2 (Half image size (Default)*	(c): *1/4 (Quarter image size)*

Figure 5-28 UAV different point density

b) Trees canopy and Keep-roof

This has been addressed by automatic classification of the data processing software and exporting the other classes without tall trees class **(figure 5-29**). The algorithm has keep-roof program that has parameter setting to keep the roof at 0-75 degrees slope and filter others by connected component at 90 degrees slope.

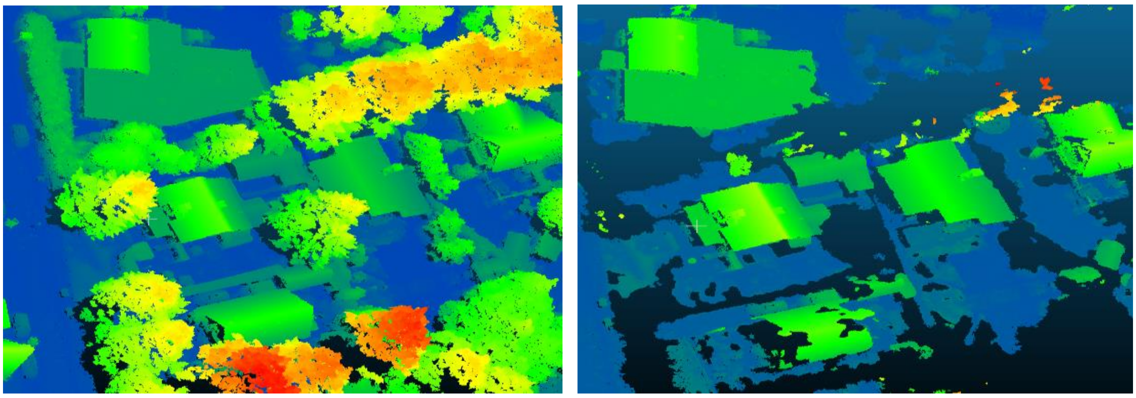


Figure 5-29 Left: Trees canopy before removal; Right: Missing data information after trees removals

c) Missing data information

The algorithm was designed to take care of the missing data information to some degree. The **figure 5-30 (Left)** below shows example of missing data information and how the algorith has reconstructed the missing roof segment data in the final 3D buildings **(Middle)** and compared to the same ALS buildings **(Right)** which had the information since the lidar could penerate the canopy . This shows clearly the the missing data can be reconstructed without omission of the segment or distortions of the roof, **however** it depends on the amount of the missing segment, if the whole segment has no data, the roof will take a flat shape at the walls height.

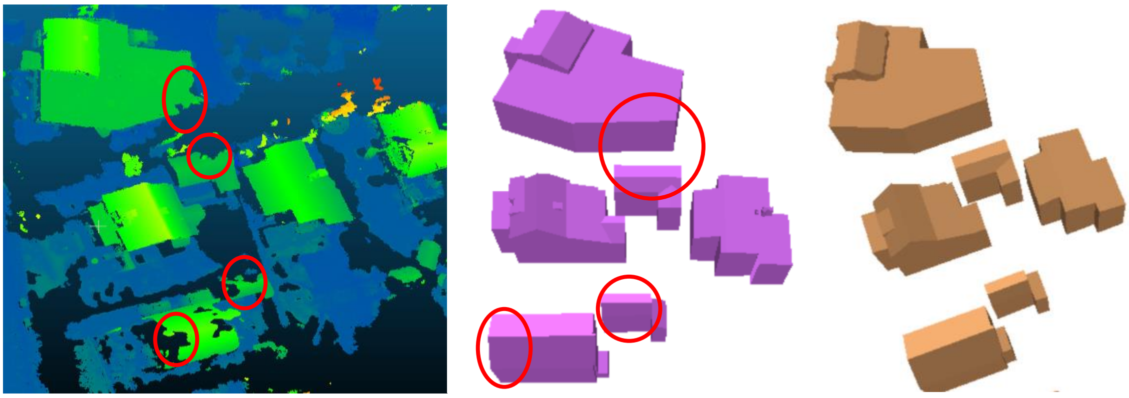


Figure 5-30 Left: Missing data information; Centre: UAV Reconstructed models; Right: Compared ALS buildings

d) Over/under segmentation

This was taken care of by parameter settings to make sure that, depending on the point density the right min-segment size and distance to the max plane was set. Noise filter also gave more smooth and non-spikes 3D buildings.

5.11. 3D buildings and Evaluation

5.11.1. Comparing the two models from ALS and UAV point clouds by visual interpretation

The two 3D building models from the two datasets were displayed **(figure.5-31)** and any difference of the two models were clear. Having satisfied the data accuracy of the UAV against ALS in horizontal and vertical extents, the reconstructed models were compared visually to see what different can be brought about by one model from the other. **In figure 5-31**, the UAV Models (left) has some dormers which are not on the ALS models (Right). By looking, it shows the difference of the two models on the roof and this can be evidence what has been captured by UAV data and what has not been captured by the ALS data and the difference in volume can also be evaluated visually for those extra features captured.

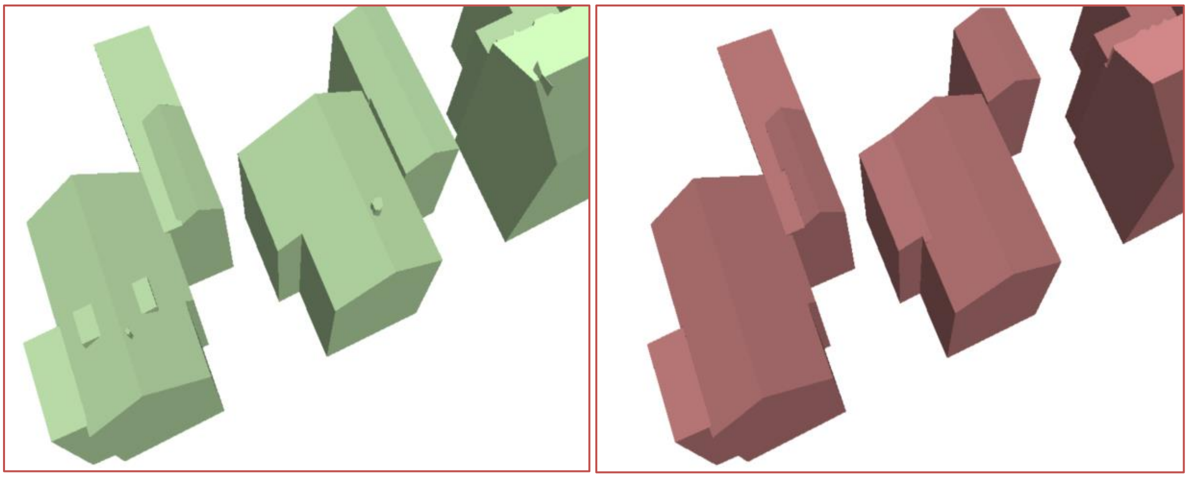


Figure 5-31 UAV and the ALS visual 3D building interpretation

5.11.2. Comparing two model of ALS and UAV point clouds by overlaying their roof planar contours

Since the final 3D model is determined by the segmentation results, an overlay of the roof layers was done to compare the difference of the two building models from the UAV and ALS point clouds based on the visual buildings on the orthomosaic **(figure 5-32)**. The red contours are for the ALS and the green contours are for the UAV, the final models of the can be seen to be agreeing. The blue circle mismatch seen on the overlay, is as a result of the UAV building at that time had been expanded from the previous ALS building since the datasets were not taken at the same time. The orange circle indicates that the UAV building had an under-segmentation at that parameter setting which later could be done with a different parameter setting.

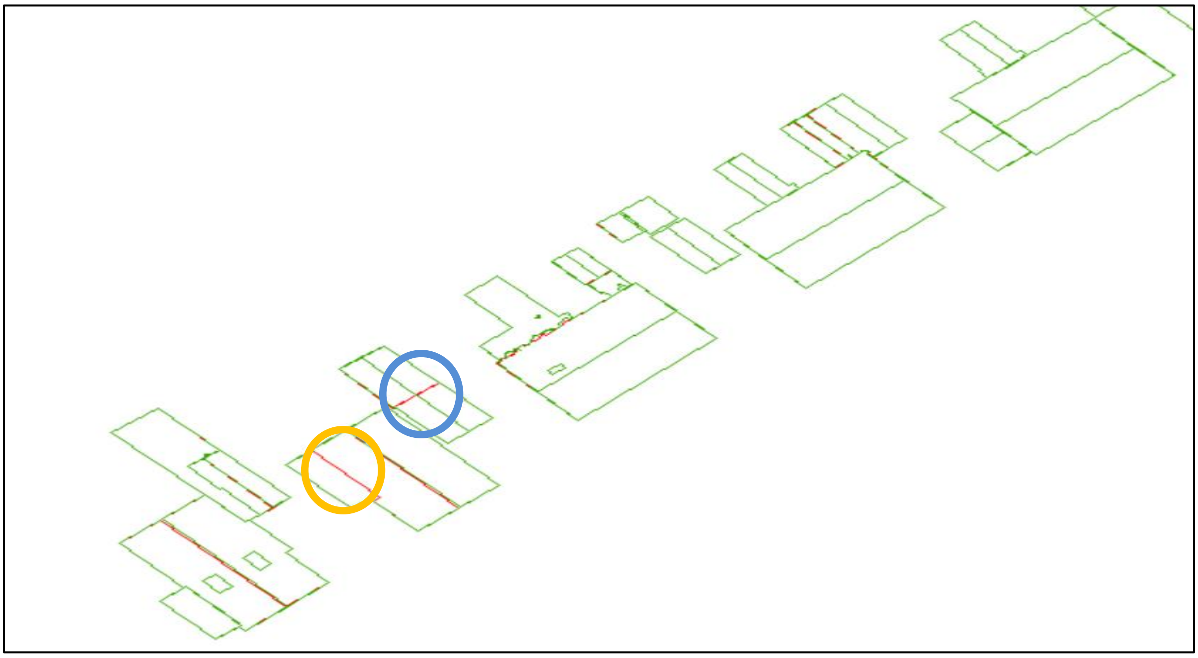


Figure 5-32 An overlay of the segmentation contours to compare the final model

6. CONCLUSIONS AND RECOMMENDATIONS ON UAV 3D BUILDING RECONSTRUCTION

In this research, UAV and ALS 3D models from point clouds has been reconstructed and compared. Accuracy evaluation of the UAV point clouds for a complete and accurate 3D models has been analysed too. Surprisingly it has shown that dense point clouds from the UAV are reliable and can reconstruct a 3D models given the good quality images of high resolution, good overlaps, GCPs and in areas free of occlusions since the missing data in such areas is still evident. Using the proposed algorithm by B. Xiong et al., (2016), it can be agreed indeed the results were as good as compared to the ALS results and the algorithm was able to recover part of lost segments due to lack of data information. However, it was seen that the UAV cannot captured point clouds under trees and shadows and this still, remains a challenge for missing data information. For this research, the interest was the roof top reconstruction and the walls were assisted by the 2D image information. So, the overlaps were too much if the only used points were for the roofs only and this does not reduce on the cost. In the future to cut down on the cost, the roof points can be captured with reduced overlaps like the traditional photogrammetry and at nadir only. After all it seems we can leave the 3D building reconstruction to UAV point clouds in the future where there are no occlusions (of trees and shadows). With different parameter setting, 94% properly modelled buildings can be achieved. It won't end without noteworthy in noise filtering, depending on how many features the user wants to see on the final building, the noise filter has been applied and shown that if unwanted, chimneys and other features like breather vents can be ignored easily. Nevertheless, the results as compared to the ALS 3D buildings were reconstructed but 3D modelling is still a challenge requiring many processes.

Answers to the research questions

- Are the 3D building models from UAV point clouds more cost effective and accurate enough to replace the lidar point clouds?

  After many tests and analysis of UAV point clouds through point density, triangulation RMS, best plane fit for noise, running a profile and many others, it can be concluded that the UAV point clouds are accurate enough to replace ALS point clouds. In terms of cost effective, UAV point clouds with such big overlaps leading to so many images come with a cost and not cheap. If the overlaps can be minimised, then UAV point clouds can be cost effective than ALS data

- To what extent can UAV dense point clouds reconstruct a better 3D building model as compared to lidar point clouds?

The final models have been compared, UAV has shown to give more roof details compared to ALS building. There is over-segmentation of UAV point clouds as compared to ALS point clouds which determines the final 3D buildings, this has been seen together with under-segmentation to ALS point clouds as well. When it comes to missing data information for 3D modelling, UAV point clouds has shown it is heavily affected by trees and shadows that it can not generate point clouds under those conditions. In the cases where the walls are needed, UAV has shown it can capture the walls at 360 degrees view and a complete 3D building of point clouds can be achieved.

- Can facades generated from UAV point clouds improve the geometry of the 3D building?
  Facades have been generated by UAV oblique images, the real building extent has also been seen where there is a roof hang. The facades will improve the geometry if they can be automatically detected. It has been seen in this research that UAV oblique point clouds can generate a complete 360-degree view of a building facades plus nadir roof points, and integrated in to the building model. The problem at this research it was demonstrated manually, if done automatically by segmentation and contour generation just as the roof and this time not snapped perpendicularly but parallel, it will define the real extent of the building.

- What is the best algorithm to reconstruct a correct and true to reality 3D building model that meets the purpose of many application?

  The algorithm by Xiong et al 2016 has been used and prooted to detect roof contours effectively and reconstructing LOD2 buildings models from both UAV and ALS point clouds, then only the roof furnitures will be represented. For a 3D building which is true to really, a LOD3 representation is required. For an algorithm to reconstruct a LOD3 building it will require the recognition of the wall among several windows and doors. In this case, geometry information is not enough , it will reqiure to integrate color and may be intensity values of the point clouds.
- What are the requirements for the generation of an optimal UAVs point clouds, and how can this be translated to the flight path planning?
  UAV point clouds has been generated at different densities, and most of the overs ranged between 85-80% forwardlap and 85-60% sidelap. The ALS 15pnts/m^2 has shown the limitation of detecting most of the roof furniture like dormers and chimneys, and this calls for more point per square area. This research proposed a traditional photogrammetric overlap which has the reduced overlaps without compromising on the point clouds quality. To be more precise, a maximum of 50 pnts/m2 will be sufficient for roof points to capture features like dormers and if additional small features are needed, then more are need.

Recommendations:

Furthers research into automatic façade detection is needed, if the proposed algorithm can automatically detect the roof planar contours and snap them to the footprint maps perpendicularly, then the facades contours can be snapped to the 2D planes parallel to the walls.

It has been said and proved the bigger the overlaps, the more accurate is the image matching, but to reduce on the cost of the UAV images the overlaps can be reduced when only roof point clouds are to be used, the overlaps should be reduced even in clear open areas where there are no occlusions, like the case of City Hall Dortmund building.

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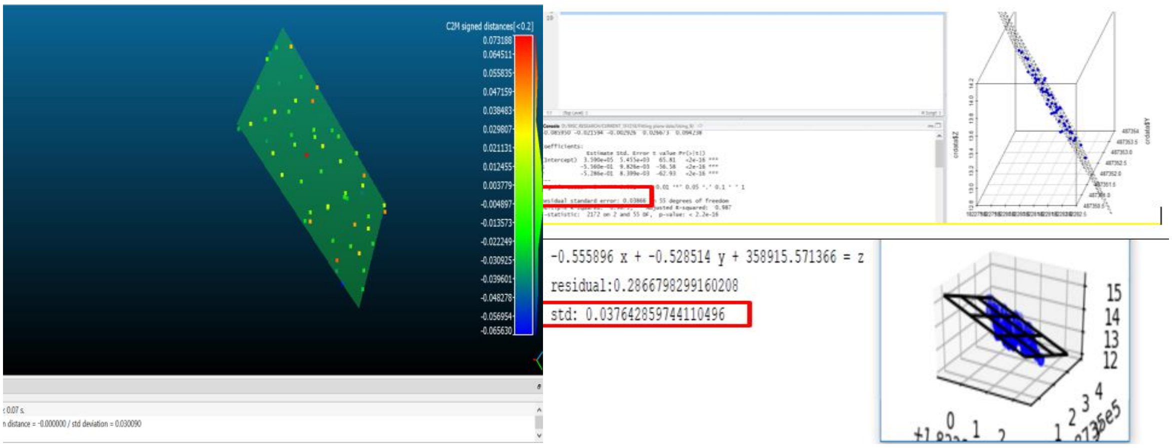
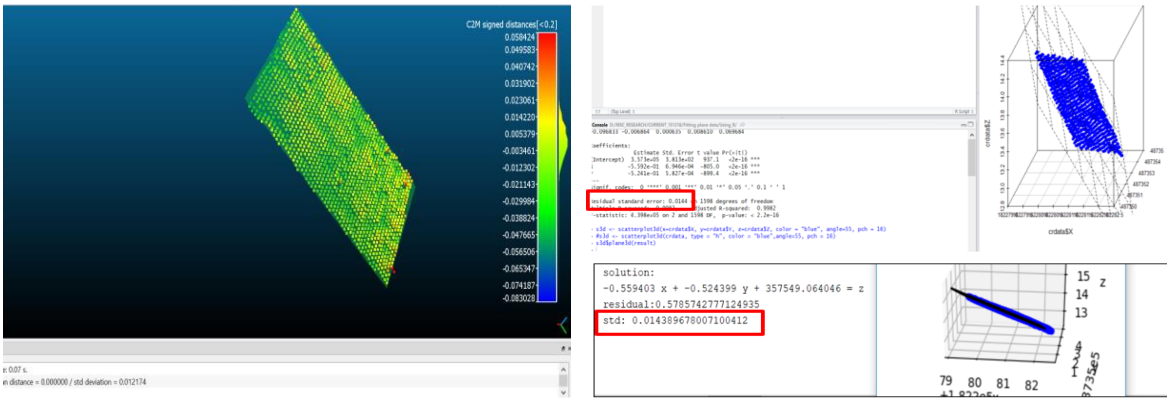
APPENDIX

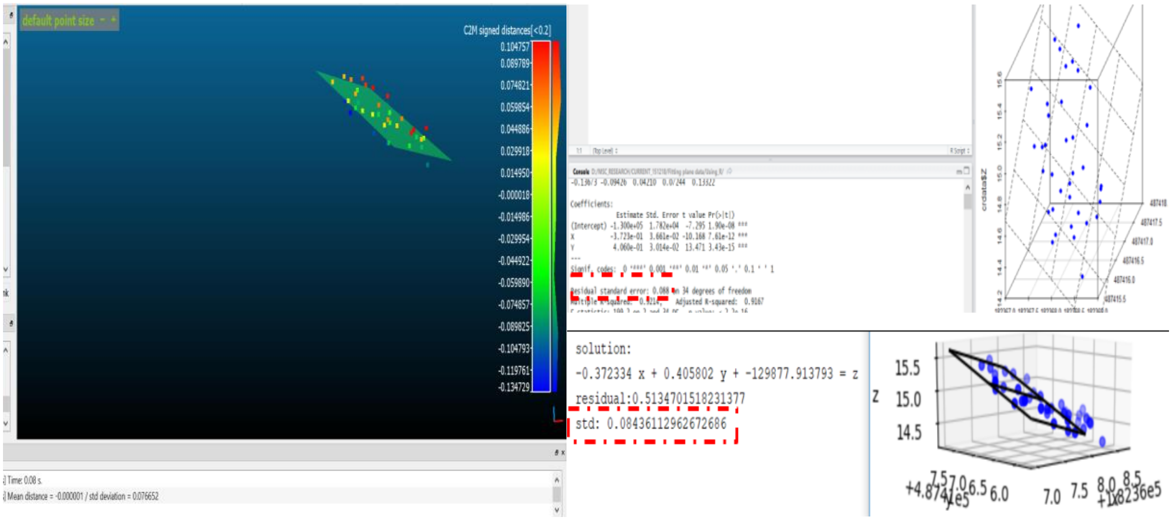
Appendix: Results for internal accuracy assessment by fiiting a plane to the point clouds



a) ALS grey1-std 0.0300 for CloudCompare, 0.0386 in RStudio and 0.0376 in PyCharm

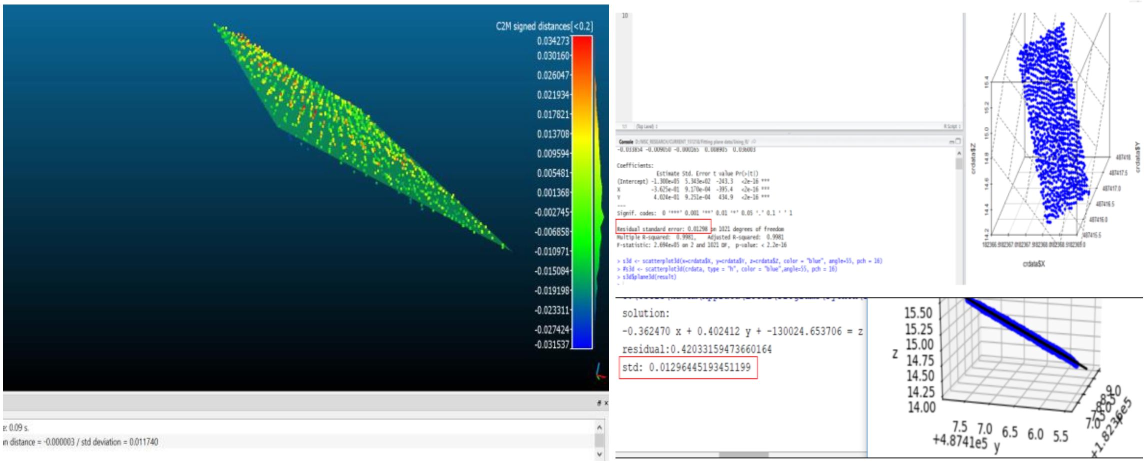


b) ***UAV grey1 – 0.012 in CloudCompare, 0.0144 in RStudio and 0.0144 in PyCharm***

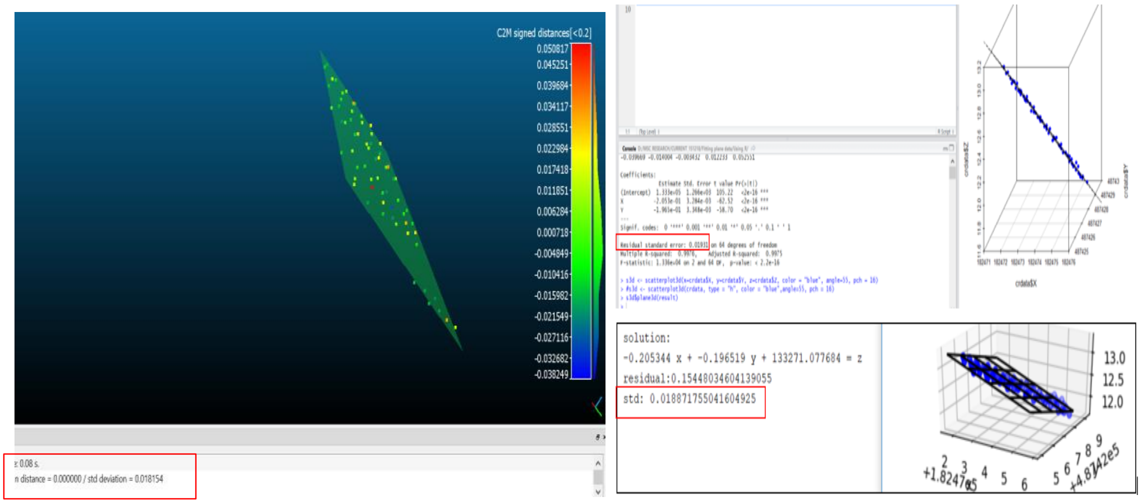


c) ALS red1-0.0766 in CloudCompare, 0.088 in RStudio and in PyCharm -0.0843

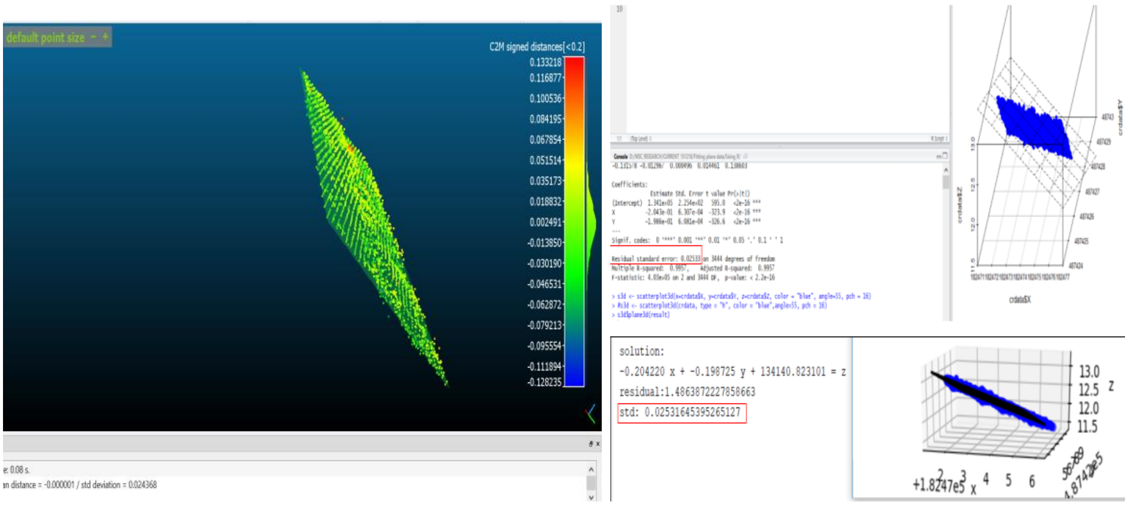
Figure A 1:



d) UAV red1: In ***CloudCompare*** 0.0117, 0.129 in RStudio and 0.0129 in PyCharm

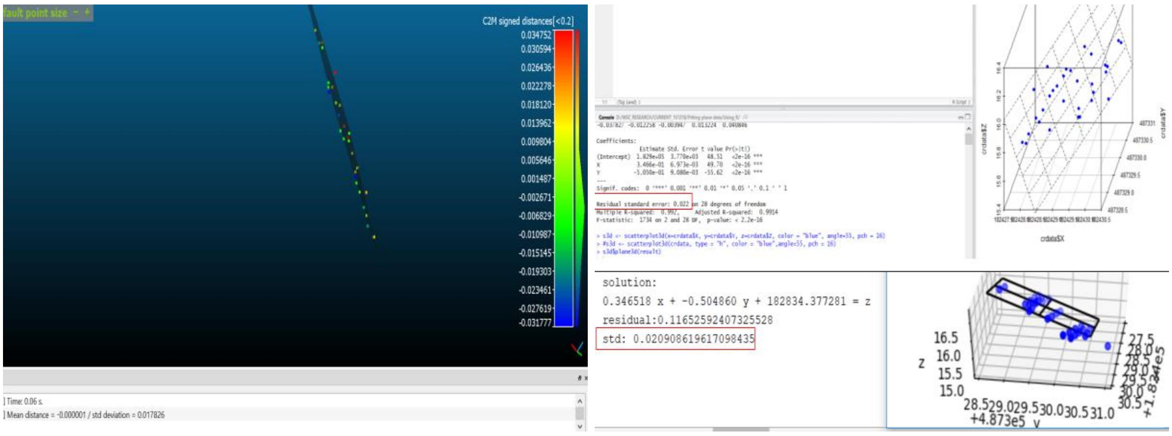


e) ***ALS grey2:*** In ***CloudCompare 0.0182, 0.0193 in RStudio and 0.0189 in PyCharm***

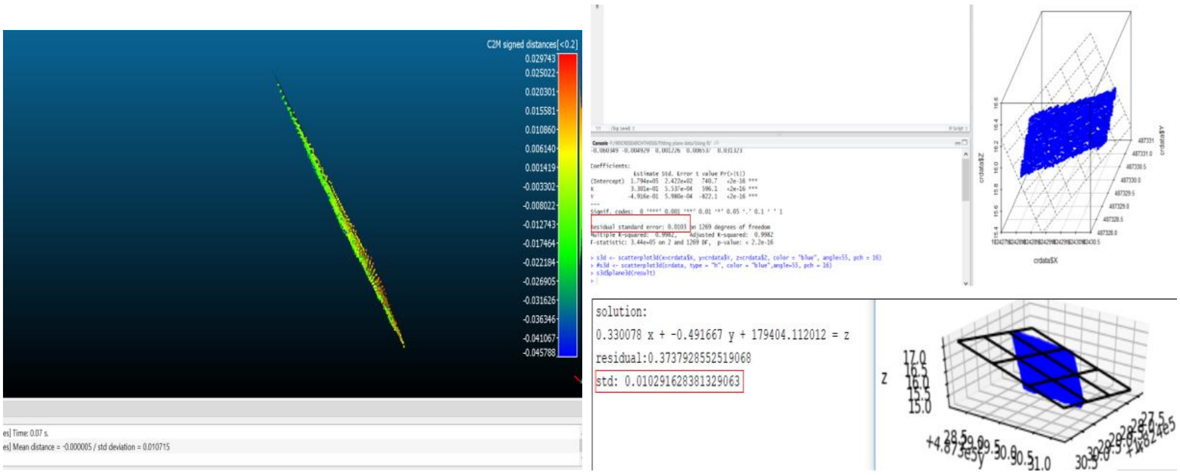


f) UAV grey2: In CloudCompare ***0.0243, 0.253, RStudio and 0.0253 in PyCharm***

Figure A 2:



g) ***ALS red2: 0.0178 in CloudCompare, 0.022 in RStudio and 0.021 in PyCharm***



h) ***UAV red2: 0.0107 in CloudCompare, in RStudio 0.0103 and 0.0103 in PyCharm***

Figure A 3