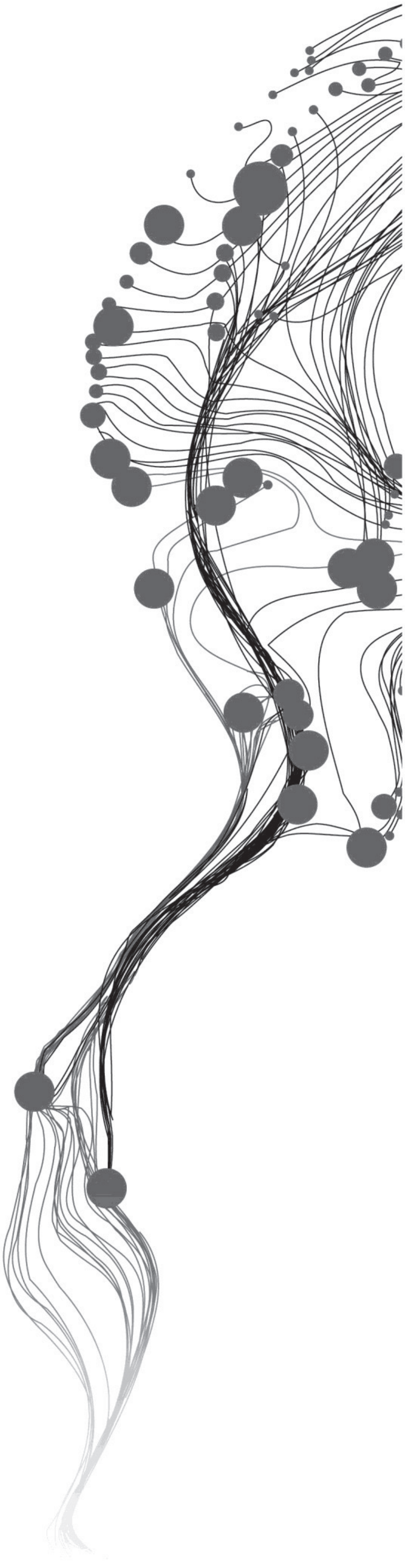
AUTOMATIC REGISTRATION OF ARCHITECTURAL (CAD) MODELS OF BUILDINGS TO AIRBONE IMAGES

BIRANE DIA
March, 2014

SUPERVISORS:
DR. M. GERKE
PROF. MG. VOSSELMAN



AUTOMATIC REGISTRATION OF ARCHITECTURAL (CAD) MODELS OF BUILDINGS TO AIRBONE IMAGES

BIRANE DIA
Enschede, The Netherlands, MARCH, 2014

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Geo-Informatics

SUPERVISORS:
DR. M. GERKE
PROF. MG. VOSSELMAN

THESIS ASSESSMENT BOARD:
Prof.Dr.Ir. A. Stein (Chair)
Dr.Ir. B.G.H. Gorte (External Examiner, Delft University of Technology)

DISCLAIMER
This document describes work undertaken as part of a programme of study at the Faculty of Geo-Information Science and Earth Observation of the University of Twente. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the Faculty.

ABSTRACT

3D to 3D registration is an important process in computer visualization. This visualization entails the use of CAD model which has become important in the process of comparing and combining the 3D datasets. The automation of many applications in computer visualization is driven by the registration of a CAD model and a sensed 3D dataset. Image-based point cloud is competitively becoming an alternative to laser point cloud owing to its full automation, and reliable accuracy for most applications such as building construction, object identification, and damage assessment. Notwithstanding the inherent disadvantages of image-based point cloud, it is generally noisy. This research investigates the adaptability of feature-based matching to overcome the problems image-based point cloud such as noise. Prior to the feature-based registration of the 3D datasets, a point cloud was generated from a set of images using SFM and PMVS, while CAD model was obtained from the same set of images with the aid of Imagemodeler® software. We extracted and matched corresponding 3D features from the CAD model and point cloud of the same object. The completely independent processes of creating these two datasets lead to some offsets or discrepancies between the CAD model and the point cloud. Given the type of datasets used, results indicate correctness and high completeness of the matching process following the low average residual, standard deviation and angle difference between matched features after the registration. This research has confirmed the limitation of applying distance or angle difference as matching criteria between corresponding features for registration purposes. Furthermore, an up-to-date and high quality CAD model is also important. The approach to this research has proven that feature-based registration is a reliable option against noisy and occluded datasets. However, the accuracy of the registration depends on the nature of extracted features and the correctness and completeness of the matching process.

Keywords: automatic registration, image based point cloud, dense matching, UAV, CAD model.

ACKNOWLEDGEMENTS

IN THE NAME OF ALLAH ALMIGHTY, THE MOST MERCIFUL AND BENEFICIENT.
A special thanks to my family. Words cannot express how grateful I am to my father ElHadj Djibril Thiam, to my Mother Adja Todj Kebe for all of the sacrifices that you've made on my behalf.
I would like to express my gratitude to my supervisors DR. M. GERKE, PROF. MG. VOSSELMAN for the useful comments, remarks and engagement through the learning process of this master thesis. I would also like to thank other members of the EOS department, Dr. K. (Kourosh) Khoshelham, Dr. ir. S.J. (Sander) Oude Elberink, PHD (Bashar) Alsadik, PHD (Anand) Vetrivel, members working as a team and always ready to answer my questions…making no difference they are supervising my work or not.
I'm grateful to the Government of the Netherlands and the hospitality and kindness of the Dutch people.
During my stay in ITC, I had to the opportinuty to meet many colleagues from many different countries. But I would like to thank my friends (Sajid) Anwar, (Adegoke Ige) Aladeboyeje, and Yu from respectively Pakistan, Nigeria and China. Brothers thanks for your company and advices all over one and half year especially when I was in doubt.
At the end I would like express appreciation to my beloved wife Mame Bousso Gueye for her support and sacrifices while I was away. Thanks also to all my sisters and brothers.

TABLE OF CONTENTS

1. INTRODUCTION 1
   1.1 Motivation and problem statement 1
   1.2 Research identification 2
2. LITERATURE REVIEW 5
   2.1 Data acquisition 5
   2.2 CAD models 8
   2.3 3D/3D registration 9
3. METHODOLOGY 17
   3.1 Point cloud planar segmentation 17
   3.2 Methodology 17
4. IMPLEMENTATION RESULTS AND EVALUATION 29
   4.1 Description of the datasets 29
   4.2 Preprocessing of the data 30
   4.3 Extraction of features 31
   4.4 Computation of segment parameters 32
   4.5 Matching result 33
   4.6 Registration results 35
5. ACCURACY ASSESSMENT AND DISCUSSION 37
   5.1 Evaluation of the matching result 37
   5.2 Accuracy of the registration 43
6. CONCLUSION AND RECOMMADATIONS 51
   6.1. Conclusion 51
   6.2. Answers to the research questions 51
   6.3. Recommendations 52

LIST OF FIGURES

Figure 1.1: Point Cloud data 4
Figure 2.1 3D reconstruction overview 7
Figure 3.1: General methodology workflow 19
Figure 3.2: Matching strategy for first estimation of corresponding planes 23
Figure 3.3: Strategy of selecting final matching table 25
Figure 3.4: Graph of translation in x-axis against residuals 27
Figure 4.1: Raw data point cloud 29
Figure 4.2: 3D CAD model 30
Figure 4.3: Point cloud after segmentation. 31
Figure 4.4: Examples of extracted segments from Point cloud 32
Figure 4.5: Examples of planes of final matching table. 35
Figure 5.1: Histograms of residuals between registered corresponding planes pairs. 44
Figure 5.2: Point cloud shifted by 5m and vertices of CAD planes model before registration (a) and after registration (b) 46
Figure 5.3: Point cloud rotated by 10 degrees and vertices of CAD planes model before registration (a) and after registration (b) 48

LIST OF TABLES

Table 3.1: Examples of possible combinations of 3 non parallel corresponding pairs (numbers given are segments Ids) 26
Table 4.1: Selected CAD planes. 33
Table 4.2: Result of final matching table. 34
Table 4.3: Average residual, average standard deviation, average angle difference of corresponding pairs CAD-UAV of final matching table 34
Table 4.4: Result of six transformation parameters: 3 rotation angles, 3 translations. 36
Table 4.5: Result of mean residual (mean distance) and mean standard deviation between points of each UAV plane and the corresponding CAD plane and their standard deviation after registration. 36
Table 5. 1: Reference Matching Table (manually edited) 38
Table 5. 2 Results of input n:m matches 39
Table 5. 3 Evaluation Result 39
Table 5. 4: Results removing CAD plane 11 39
Table 5. 5: Results removing CAD plane 71 40
Table 5. 6: Evaluation Result 40
Table 5. 7: Results Shifting point cloud by 2m 41
Table 5. 8: Evaluation Result 41
Table 5. 9: Results rotation point cloud by 5 degrees 42
Table 5. 10: Evaluation Result 42
Table 5. 11: Mean residual (mean distance) and mean standard deviation between points of each UAV plane and the corresponding CAD plane and their standard deviation. 43
Table 5. 12: Matching Table 46
Table 5. 13: Final Matching table 46
Table 5. 14: Result of six transformation parameters: 3 rotation angles, 3 translations. 46
Table 5. 15: Mean residual (mean distance) between points of each UAV plane and the corresponding CAD plane for each corresponding CAD-UAV plane pair. 47
Table 5. 16: Mean standard deviation between points of each UAV plane and the corresponding CAD plane for each corresponding CAD-UAV plane pair. 47
Table 5. 17: Result of comparison between the registration of the initial position and the registration after the 5m shift 47
Table 5. 18: Matching Table 48
Table 5. 19: Final Matching Table 48
Table 5. 20: Result of six transformation parameters: 3 rotation angles, 3 translations 49
Table 5. 21: Mean residual (mean distance) between points of each UAV plane and the corresponding CAD plane for each corresponding CAD-UAV plane pair. 49
Table 5. 22: Mean standard deviation between points of each UAV plane and the corresponding CAD plane for each corresponding CAD-UAV plane pair. 49
Table 5. 23: Comparison between the registration of the initial position and the registration after 10 degrees rotation 49

1. INTRODUCTION

1.1 Motivation and problem statement

Unmanned Aerial Vehicles (UAVs) are portable devices which can be used to acquire very high resolution data (images), of any scale and at a low cost. The advent of UAV technology has led to an increase in the number of image processing applications. Applications involving images of building and its 3D CAD model are now common. Application areas of UAVs in the European Union (EU) include construction site monitoring, and disaster assessment among others. However, to realize the benefits of UAV applications as in the context of the EU project RECONASS (Reconstruction and Recovery Planning: Rapid and Continuously Updated Construction Damage, and Related Needs Assessment), actual images of buildings need to be co-registered with a geometric description of the same 3D CAD model.

Registration can be viewed as a process by which data obtained from different conditions are transformed and aligned. The conditions may be different times, sensors or sources (Kim et al., 2010). Once the registration is achieved, many applications could be realized like the monitoring of construction progress with the registration of point cloud obtained from construction site and its 3D CAD model (Bosche, 2010). In addition, it is applicable to computer vision operated with robotic applications (Zitova & Flusser, 2003). However the techniques used during registration of images of building and its 3D CAD model are diverse.

David et al. (2003), have examined the direct registration of images to 3D CAD model (2D/3D)by attempting to use lines to simultaneously solve the problem of automatic registration, high occlusion, and high clutter. Even though the method succeeded in addressing these two issues, its limitation arises from the initial guess of the model pose which is not accurate. Furthermore, the proposed algorithm had major limitation in determining the number of guesses to be done before finding a good pose. These problems with the 2D/3D registration have led to the exploration of new methods.

Today with the development of science and technology and the availability of new software with high processing and big storage capabilities, new techniques are being used. One of those techniques is the combination of all images by dense matching to obtain a 3D point cloud (Gerke, 2009). The registration is now 3D/3D involving the 3D point cloud and the 3D CAD model. However 3D/3D registration automation may be a challenge. The datasets involved are in different formats: points without topological relationship and geometric representation with topological relationship (Ip & Gupta, 2007). Another problem to surmount when registering point cloud data and 3D CAD model is the difference in level of details and accuracy between the two datasets (El-Hakim et al., 2005). In spite of these challenges, they have been some tests and case studies.

The use of 3D/3D registration has been applied by many scientists. Ip and Gupta (2007), examined the use of a point cloud of an artefact to find its CAD model in a database. They showed that matching CAD models and point cloud data could be used for searching a CAD database to find a specific machine part. But the major limitation of the method is that, it can only be applied to small parts which are very distinct and cannot be extended to buildings which are generally similar when they are located in the same area; even though this method could itself be very efficient in cases of occlusion. 3D Modelling concerning historical architectural sites could involve different types of data from different sources such as laser data, 3D CAD data, and photogrammetric data. One of the important steps to model an architectural site is to register all the 3D models created from these different datasets (El-Hakim et al., 2005). Although El-Hakim et al. (2005), mentioned the use of Laser data in theory, they did not really use this data in the case study. Bosche (2012), proposed an alternative to the standard point base registration techniques by introducing a novel semi-automated plane-based registration system which performs a coarse registration of laser scanned 3D point cloud with 3D model. However the extraction of laser planes was semi-automatic and the plane matching was manual. Therefore, a reliable fully automated solution (between point cloud data and CAD model data) is still lacking.

The direct registration of images (2D) with 3D CAD model; that is 2D/3D method still faces many challenges. Although the 3D/3D may be an alternative, a careful look at the two methods of registration (2D/3D and 3D/3D), as tested by Stamos et al. (2008), indicates that they are complementary. Hence, 3D/3D registration could be an input for the first initial guess of parameters for the 2D/3D registration. Nevertheless, all these will only be possible if we solve the deficiencies underlying the 3D/3D registration. The problems mentioned above has proven that there is still room for improvement which can be addressed by automatic registration.

1.2 Research identification

With the increase in the number of natural and manmade disasters such as earthquake, typhoons, floods and tsunamis, post disaster assessment, automated image registration is of major concern. Chiroiu et al. (2006), described an inventory of techniques used like optical imagery from high resolution satellite, to radar imagery including airborne laser. Use of satellite images may be affected by cloud and smoke or limited by daylight and low revisit frequency. Also, SAR images have limitations because of considerable noise level associated with the processing and interpretation of complicated images (Eguchi et al., 2010). Point cloud obtained from direct laser scanning of buildings (Li et al., 2008) or from dense matching of airborne or UAV images (Gerke, 2009; Wang et al., 2011) has the advantage of showing point data but also detailed information like roof and also façade even though it may be limited by daylight.

Chiroiu et al. (2006), used datasets collected before and after an earthquake to described the methods used in damage assessment like damage-based photo interpretation or using semi-automatic techniques. Nowadays, many cities have 3D CAD models of at least some key buildings and for this, a model-to-point cloud registration would be needed before any damage detection algorithm can be developed.

Most works done on registration of point cloud and 3D CAD model were found in construction automation and monitoring applications. The data acquisition technique used for the point cloud is Terrestrial Laser Scanning (Bosche, 2012; Kim et al., 2010; Kim et al., 2013).

We can see that none of these studies took advantage of using UAV generated images. However, after showing the drawbacks of TLS data, Golparvar-Fard et al. (2009) used point cloud from image-dense matching in construction site monitoring by registration of 3D point cloud to a 3D/4D model. Since the images were taken from the ground, the limitations found with TLS data was that only features like the façade and interior were visualized, while the roof was not captured in the dense point cloud imagery. Therefore, the registration of dense point cloud from imagery of building with a 3D CAD model and its applications is still a field to explore.

Brenner and Dold (2007), demonstrated an improved method for fully registering laser scans commencing with extraction of planar patches. With a view to reduce the research space, the authors deployed a combination of hierarchical test with angular constraint. According to Brenner and Dold (2007), this method could be extended to any scene having planar features as in the case of buildings. However they used infinite planes which does not guarantee effective match.

This study attempts to overcome these limitations, by designing an automatic registration algorithm between CAD model and point cloud from UAV using dense matching (showing façade and roof) with minimal manual intervention and minimal constraints. The algorithm should integrate both the occlusion problems and efficient search strategy.

1.2.1 Research objectives

Our main objective is to set up an algorithm which will perform an automatic registration between the 3D CAD model and the 3D point cloud generated from UAV images by dense matching.

The following sub-objectives will help reach the main objective:

1. To determine features which are suitable for both CAD model and point cloud in the perspective of matching;
2. To determine best strategies to match corresponding features with an efficient and robust search strategy included;
3. To derive the transformation parameters; and
4. To evaluate the accuracy of the registration process.

1.2.2 Research questions

(a) What are the available techniques for 3D/3D registration?
(b) Which of these are more suitable to both 3D CAD model and the 3D point cloud?
(c) In case of feature based registration, which features are more robust to occlusion problems?
(d) Which search strategy is more suitable for looking for corresponding features to match?
(e) How accurate and successful is the registration algorithm especially with occlusions/gaps?

1.2.3 Assumptions

We use UAV to take the images. From the images, we generate dense point cloud as shown in Figure 1.1. Since on board we have GPS so that UAV images can be oriented with quite a high accuracy but the location with respect to coordinate frame is uncertain because of limited onboard GPS positioning capabilities. With the CAD model and Google maps, we can approximately co-register the model and the map. Hence we can know the position of the building with an accuracy of 3m to 4m.

Although the GPS and Google maps are not very accurate we assume to know the coordinates of the point cloud and the coordinates of corners of the building. Further the scales are unknown, but in our case we assume to have no scale difference between both datasets. So we assume an initial coarse registration.

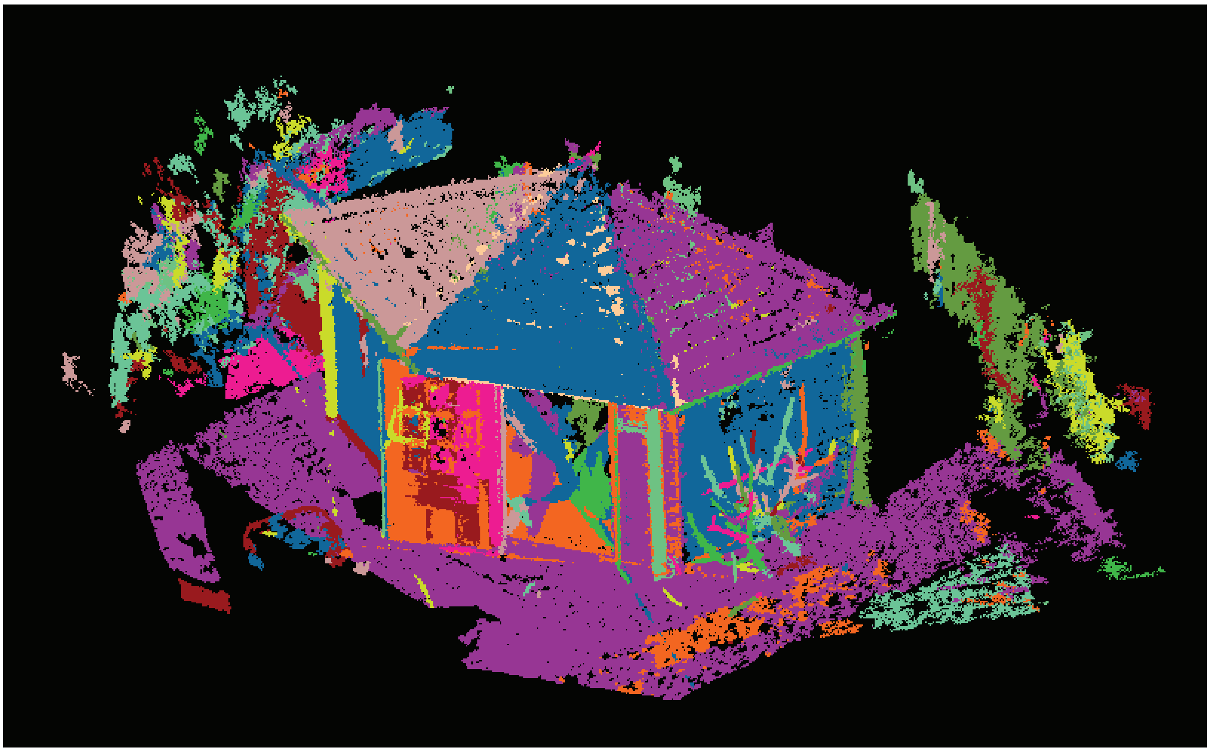


Figure 1.1: Point Cloud data

1.2.4 Innovation aimed at

Most of the works done concerning the automatic registration between CAD model and point cloud was done using Terrestrial laser scans data.

The innovation aimed is:
An automatic algorithm that registers 3D CAD model and the 3D point cloud from UAV dense matching with very limited manual operation.

2. LITERATURE REVIEW

In this chapter we introduce the theoretical background required for this research. The chapter opens with the description of the types of inputs we have in this research in Section 2.1 named data acquisition where the importance of UAV, imaged based point cloud are elaborated. CAD models are described in Section 2.2. Section 2.3 highlights some terminologies used throughout this research with a broad description of 3D/3D registration its working principle, the mathematical background behind it. An overview of the existing methods has also been given in this section.

2.1 Data acquisition

2.1.1 UAV and high resolution images

The unmanned Aerial vehicle (UAV) is a more affordable technology. With this promising technology, it is possible to acquire very high resolution data (images) of any scale at a low cost. It is commonly applied nowadays. UAV has been defined by Remondino et al. (2011) as a generic apparatus conceived to function without human pilot onboard. It is an aircraft which is portable and light. The cost of traditional manned aircraft and its operability depends on weather conditions such that UAVs have become more feasible alternatives (Hassan et al., 2011). The low altitude flight done by UAVs allows it to avoid most of the problems like atmosphere interference, handicapping the traditional photogrammetric methods (Manned craft and satellite). So UAVs are more reliable. UAVs were first used for defence and military purposes, but are increasingly used in a wide range of applications in many emerging fields (Lelong et al., 2008).

Nevertheless, UAVs have some challenges or limitations to overcome. The main limitation is with the problem of GNSS/INS systems used on board UAVs. This low cost and inaccurate device has a negative effect on the accuracy of the images of UAV (Remondino et al., 2011). Indeed the weight and dimensions of the sensors of UAV have posed limitations to the quality of data from UAVs (Kim et al., 2013). Notwithstanding the advantages of low weight and affordable price of UAVs, attempts towards improving the quality of its IMU and incorporation of RTK techniques create a trade-off between affordability and quality of the technology (Remondino et al., 2011). Hence, more solutions are also under investigations among which is the experimentation of smartphones and its numerous imaging and geo-processing capabilities (Kim et al., 2013).

The other problem of UAV is weather related. For example it becomes difficult to use this technology ins a raining or windy environment. The UAV is designed to fly at a very low altitude of around 20 to 100m for the purpose of obtaining very high resolution images. The implication is that images are generated at different scales and with geometric deformations (differences in resolution and viewing angles). This implies extra pre-processing of images for their correction (Lelong et al., 2008). Despite these drawbacks, UAV is having an increasing important role with many applications especially in forestry and agriculture, archaeology and cultural heritage, environmental surveying, traffic monitoring, 3D reconstruction. (Remondino et al., 2011).

Remondino et al. (2011), enumerated the main types of UAVs among which includes the unmanned combat autonomous vehicles, which are special UAV design for military purpose. According to Remondino et al. (2011), the primary objectives of designing UAVs were for military use. These military tasks could be surveillance and spying by taking aerial photographs. It can also be used as a tool for military targets. However many countries are working to come up with new regulations for the specific conditions in terms of technical specifications as well as geographical places where this unmanned vehicles could operate (Remondino et al., 2011). Hence, UAVs still have a bright future with science. Indeed its low cost and ease of operation has made it a credible alternative to expensive classical aerial photogrammetry (Remondino et al., 2011).

3D Reconstruction of historical site has always been an important task because of its role in preserving and maintenance of these sites. Laser scanning, aerial or terrestrial, could be used for 3D reconstruction. Although the accuracy of this method is very efficient, its high cost and technical sophistication in post processing has encouraged users to look for alternatives. Koutsoudis et al. (2013), proposed the use of UAV-based imaged combined with SFM and dense Multi-view 3D reconstruction software. In a comparative study, of the two technologies (Laser and image based), he showed that UAV imaged based could be also very accurate for 3D reconstruction.

The limitations of traditional aircraft with high altitude which are not compatible with large scale mapping have prompted the use of UAV. Indeed these low altitude flying devices like UAV and RPV (Remote aerial vehicle) were used and tested successfully for the conduct of archaeological surveys in the Italian piedmont region (Chiabrando et al., 2011). Gruen et al. (2005) further identified the challengers which are specific to UAV to include strong winds, insufficient overlaps and lack of contrast in images and how to solve them.

Its ability to deliver very high temporal and resolution image in record time has given UAV a leading advantage compared to traditional photogrammetric image acquisition tools (Remondino et al., 2011). However, it is not a matter of opposing the two methods but rather to see their complementarity (Remondino & El-Hakim, 2006).

2.1.2 Image based point cloud

In recent years, the interest for image based point cloud has steadily increased. This is principally due to the availability of high resolution images but also manned aerial images because data from laser scanner are still expensive or inexistent (Alobeid et al., 2010). Generally there are two sources for point cloud: image based point cloud and laser based point cloud. Even though 3D scanners are becoming popular and progressively used in many applications thanks to a steadily decreasing cost (Bosche, 2012), imaged based point cloud is still a widely first choice due to its numerous advantages like portability, affordable cost and more important flexibility and automation (Remondino & El-Hakim, 2006).

There are many techniques and dense matching algorithms (local methods, pixel-wise matching, dynamic programming) used for the acquisition of imaged based point cloud (Hirschmuller, 2005). Brandou et al. (2007) gives examples describing 3D reconstruction using dense matching for a world heritage site like a tomb. The main steps he used are summarised using the workflow in Figure 2.1.

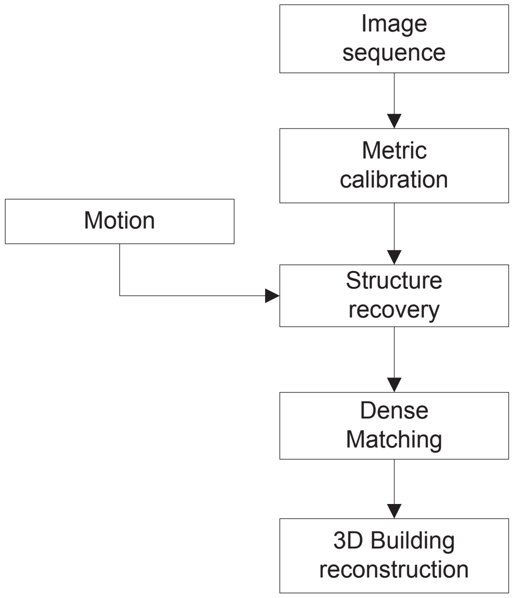


Figure 2.1 3D reconstruction overview

(Brandou et al., 2007)

The appropriate algorithm to use depends with the nature of the data available but also the result to expect. Nevertheless, Alobeid et al. (2010) have done the comparison between least square, dynamic programming and semiglobal matching by applying each in DSM generation. He concluded that semi global matching had the best results.

Generally dense matching is applied to vertical images, but it could also be done for oblique images. Unlike vertical images, this may lead to dense point cloud on vertical structures. This is due to the special properties of oblique images being able to show façade of buildings (Gerke, 2009). Cabrelles et al. (2010) concluded that the advantage of imaged based dense matching for 3D reconstruction is not only the advantage of avoiding carrying expensive and heavy equipments but also it is a successful alternative to LIDAR technology for 3D projects. But he insisted that the two technologies could be complementary in many cases.

2.1.3 Accuracy of image based point cloud (Comparison between imaged base point cloud and laser point cloud)

Terrestrial Laser Scanner (TLS) point cloud is not uniform, because unlike airborne 3D data, areas of the object to be scanned which are close to the scanner get more points than those which are away (Lam et al., 2010). On the other hand, UAV imaged based point cloud is more noisy (Gerke, 2009). Despite all this, could we use image based point cloud in place of TLS point cloud and handle the same applications and have accurate results? Westoby et al. (2012), tried to bring an answer by comparing the use of point cloud from image dense matching and TLS point cloud. He used both of them separately in producing DTM. He discovers that the TLS point cloud is slightly denser, but the result obtained from producing DTM using imaged based point cloud is as good as that of TLS even if the computation time to process the images to have the point cloud may be a concern. But this was downplayed by the low cost and automation gained from image based point cloud.

Following the same logic, Golparvar-Fard et al. (2011) compares two methods using point cloud from imagery and the other point cloud from 3D laser scanning for construction progress monitoring. Using a comparison table, he concluded that image based point cloud is less accurate than 3D laser scanner data. However if image based point cloud cannot be used when very sophisticated and precise alignment is needed, it can still be very useful for most applications like measuring deviation, or to assess overall project or even status of a post disaster site. And one can take full advantage of less cost and full automation of image based point cloud generation. In addition, Koutsoudis et al. (2013) evaluated the advantages and limitations of image based 3D reconstruction method by comparing it to many tools among them, terrestrial 3D laser scanning. He showed that measurements from UAV images based point cloud data are very accurate by comparing Euclidian distances between empirical measurements on a real monument and its Structure-From-Motion (SFM) and Dense Multi- View 3D Reconstruction photoScan data. Even if we have less accuracy with areas of low frequency of colour change or lack of strong features.

Although, most of the popular algorithms and methods, the Structure-From-Motion (SFM) and Dense Multiple View 3D Reconstruction algorithms have been implemented by commercial software, Koutsoudis et al. (2013) investigated the reliability and quality of such software to already existing solutions like 3D scanning. After giving examples of these commercial software like Photoscan, PhotoModeler scanner, Pix4D, the authors compare the results of these software against traditional methods like 3D scanning in recording archaeological sites. They concluded that with high end hardware (like cameras), the 3D reconstruction software could produce high quality results.

The image based point cloud is still very reliable, low cost and is accurate enough. Therefore it could be use to do accurate surveying but also interesting applications like the ones described above.

2.2 CAD models

With the rapid development of very efficient computer hardware but also computer aided design softwares, the use of CAD models is becoming common. The unique property of a CAD model, is that most of the projects or objects are constructed based on their CAD model. Once completed, the product is expected to be the closed to its CAD model (Bosché, 2008). Indeed many applications take advantage of 3D Computer Aided Design modelling. Most of the objects need to be model in 3D before any further process. These applications could be find in industries, civil engineering applications or damage assessment.

The realization of a CAD model is generally the first compulsory step in many processes. It is the case in automatic inspection of industrial parts which is carried out to monitor if a product satisfies all the preset specifications. Here the CAD model and a sensed 3D data (point cloud) are compared to trace the errors. The CAD model is used for these specifications and necessary mathematical information describing the shape and geometric relationship between different parts of the object (Boukebbab et al., 2007; Li et al., 2013; Prieto et al., 1999). The same idea is used in Ip and Gupta (2007) where the idea of looking for a CAD model of a specific industrial part by mean of its 3D scan is introduced when no other information like the part number is available. Here the concept of a database of CAD models is used where the 3D scan is used to search the database to retrieve its CAD model equivalent. Even though the search algorithm should be robust enough to segregate between similar parts.

Building Information Model or 3D/4D CAD model is generally available for any construction project. This as planned model with 3D point cloud acquired from the site of construction is also involved in many construction automation applications like construction progress (Bosche, 2012; Ip & Gupta, 2007; Kim et al., 2013; Mani et al., 2009). Here the use of the 3D CAD model is essential because the CAD model contains information like as planned progress but also construction schedules (Kim et al., 2013). And all these information are critical for any automation process.

The use of CAD model is common to all these applications, they also share the fact that the CAD model need to be aligned to the other dataset (generally a sensed 3D data) for any automation to be possible. Therefore to perform an automatic task, there is always a critical step: the registration of the CAD model to the 3D data. Many methods has been described and tested but each with also its advantages and disadvantages.

2.3 3D/3D registration

2.3.1 3D/3D registration

3D registration could be defined as a process by which different datasets are aligned in one coordinate system (Wang, 2013). These datasets may be from different times, sensors, or viewpoints (Kim et al., 2010)
With the advent of Unmanned Aerial Vehicles (UAV), an affordable technology, a big step has been done. Now, it is possible to acquire very high resolution data (images) of any scale at a very low cost. This has led to the increase in the number of applications with images. Applications involving images of building and its 3D CAD model are now common. However to realize applications, as in the context of the EU project RECONASS (Reconstruction and Recovery Planning: Rapid and Continuously Updated Construction Damage, and Related Needs Assessment), where we have tasks like construction site monitoring, disaster assessment among other. Actual images of buildings need to be co-registered with a geometric description of the same like a 3D CAD model.

Registration can be viewed as a process by which data which are from different conditions are transformed and aligned. The conditions may be different times, sensors or sources (Kim et al., 2010). Once the registration is achieved many applications could be realized like the monitoring of construction progress with the registration of point cloud obtained from construction site and its 3D CAD model (Bosche, 2010) , but also in computer vision with robotic applications (Zitova & Flusser, 2003). However the techniques used during registration of images of building and its 3D CAD model are diverse.

With the increase in the number of natural and manmade disasters (earthquake, typhoons, floods, tsunamis), post disaster assessment has never been so important. It is now a major research field. Chiroiu et al. (2006) gave an inventory of techniques used. One of the techniques is the use of point cloud obtained from direct laser scanning of buildings (Li et al., 2008), which could be extended to point cloud from dense matching.

Schweier et al. (2004) showed how damage information could be evaluated by comparing models of the pre and post earthquake. The author described two strategies which could be used to have the input data which consist of a CAD model of the intact building and laser point cloud before and after the damage. And a comparison of the two point cloud be used to assess the damage by detecting changes like volume difference, plane orientation among others.

Nowadays many cities have 3D models of at least some key buildings and for this a model-to-point cloud registration could be directly used to detect and evaluate the same changes. We could use UAV to have images of the building and used a dense match technique to generate the point cloud. Damage assessment, also follows the same principle, principle which states that all this applications have a common step in their process and this step is the registration between a 3D model and a 3D remotely sensed data: 3D registration.

Gressin et al. (2013) and Zitova and Flusser (2003) described the steps involved in registration of 3D datasets. The main steps are:

- Feature detection.
- Feature matching.
- Transform estimation.
- Registration

- **Feature detection.**

Feature extraction is the process by which features to be used during the registration are identified in the datasets to be registered (Doucette et al., 2013). In feature based registration, we need to study and compare the datasets to be registered and try to extract common features which may be used in the registration process. According to Besl and McKay (1992) , in 3D / 3D registration the following geometric features could be used:

- Point Sets
- Line Segment Sets (Polylines)
- Implicit Curves
- Parametric Curves
- Triangle Sets (Faceted Surfaces)
- Implicit Surfaces
- Parametric Surfaces

The obvious question is which feature is the most appropriate? Generally there is no straight answer to this question. The 3D features to use depends mainly on the type of data we have and the specific task to be performed (Ramalingam et al., 2010; Rottensteiner, 2002). The selection and extraction of features from datasets will need to be related together and extra information will be needed to carry out the feature matching.

- **Feature matching:**

Matching is a fundamental step in registration and deals with what is called the correspondence problem, i.e. how to relate the two datasets. It can be expressed as the processes of comparing two datasets in order to extract common features (Monnier et al., 2013). The flexibility of feature based matching against noise and occlusion compared to other type of matching like area based matching is prominent and one of the most reliable way to perform a registration between two 3D datasets is to find and match corresponding 3D features (Rottensteiner, 2002). Matching is also a critical step. The matching algorithm should not only look for potential correspondences but it should be able to eliminate false matching pairs of features from the two datasets (Armenakis et al., 2013). Different feature matching strategies could be adopted depending on the type of data and the aim of the registration. The matched features can allow computing the transformation parameters which will align the different datasets.

- **Transform estimation and Registration:**

To estimate the transformation parameters, we need features like points, lines or planes. The combination of features to be used depends on the datasets and the strategies adopted. Jaw and Chuang (2008), showed that we could have point based transformation model where the transformation parameters are estimated using 3D points from both datasets. We can also have line base transformation model or plane-base transformation model where lines and planes in both datasets are respectively used. The combination of different type of features like use of points in one dataset and planes in the other (point to plane) to estimate the transformation parameters has been also successfully carried out (Grant et al., 2012). Furthermore the integration of all these features point, line, plane at the same time in the mathematical model used, could be done for solving parameters. The comparison of the four methods point-base, line-base, plane base and the integration of the three have proven that the latter has better result in estimating the transformation parameters (Jaw & Chuang, 2008).

To estimate transformation parameters we need at least 3 3D corresponding non planar points, or 3 3D corresponding non parallel planes, and in case of line we need at least 2 corresponding 3D lines. Generally points are represented by its 3D coordinates, planes by normal and distance from origin and line by coordinates of 3D end points (Jaw & Chuang, 2008). For 3D similarity transformation, the parameters are a translation vector (Tx, Ty, Tz) and three rotation angles (ω, φ, $\varkappa$) and a scale to complete the 7 parameters points (Jaw & Chuang, 2008). In case of rigid transformation the scale $S = 1$.

The estimation of the transformation could be done in case of point to point registration, line to line, plane to plane registration or point to plane registration. The mathematical model and estimation of parameters when having 3 3D corresponding points is well described in Thapa (2009). However the main problem of point registration is that one point present in one dataset may not be available in the other dataset due to many reasons (occlusion, type of sensor used or different in view-points, different resolutions between datasets). An alternative to this problem is the use of point to plane registration (Salvi et al., 2007) or a plane to pane registration.

2.3.2 Registration of 3D Point cloud /3D CAD model: selection of methods

Before the plane to plane registration (Bosche, 2012; Brenner & Dold, 2007), many techniques have been experimented in registration of CAD model and point cloud. The most popular ones are the point to point registration and the point to surface registration. For point to point registration, the general idea was to perform a point to point registration (traditional or improved ICP) (Besl & McKay, 1992). First, the CAD model is converted into points to have both datasets into points. This idea was at the beginning introduced by Besl and McKay (1992) later Boulanger et al. (1996) used the same technique. But the method was improved to make it more robust to occlusion.

Boulanger et al. (1996) Method, used three algorithms: Least Median of square error (LMS) to make sure that the method could face outliers, an improved ICP and the used of quaternion method for the rigid transformation estimation. To avoid local minimum, Boulanger et al. (1996) divided the first dataset of points into small sets of points and register each subdivided dataset with the entire second dataset using at each time the quaternion method. After multiple initial transformations, the LMS estimator was then used to determine each transformation and the best one is chosen. Since this initial transformation could have only been done with inliers, it's not very reliable because it is not taking all points into account and may have excluded some outliers. To make sure that all the points are used, an ICP algorithm is used to transform the entire points of the first dataset into the second using the transformation as initial guess. This method used by Boulanger et al. (1996) was very successful. It has been used and adapted in different situations according to the geometry, complexity, size of the CAD model but also for the type of application the registration of the point cloud and the CAD model is aimed for (Prieto et al., 1999). The Boulanger et al. (1996) algorithm was reorganized and used in the field of inspection and quality control of manufactured parts. In fact Boukebbab et al. (2007) applied this algorithm for checking the conformity of the industrial parts after their production. They compared these products with their CAD model which has been used as reference to manufacture them. Here they register the point cloud of the part and its CAD model. The authors converted the CAD into STL (STereoLitography) format instead of points. The STL format will convert the CAD model into triangular facets. Each facet represented by the coordinates of three vertexes and its normal. He then uses the (Boulanger et al., 1996) method with following changes:

- Transformation of the CAD model into STL format.
- Random selection of points for use in the computation of the rigid transformation.
- ICP algorithm was used with the singular value decomposition function (SVD) until convergence

The (Boukebbab et al., 2007) method is also very robust to noise and could be a well suited method for registration of imaged based point could which is also noisy. Even though the pre-processing phase of the datasets may be a concern, other alternatives like plane to plane and point to plane registrations are being tested and applied.

2.3.3 Plane to plane or point to plane registration

Many problems and limitations were discovered with point to point registration to include necessary good initial guess; however, it does not necessarily mean that closest points between two datasets should be registered as that may lead to false correspondences. All these problems may negatively influence the performance of point to point registration. So a solution may be the point to surface registration also called point to plane registration (Xie et al., 2010).

There are many methods used in point to plane registration. Chen and Medioni (1992) used point to plane registration by finding correspondences between 3D points with normal in one dataset to 3D planes in the other dataset and register them. However here like ICP we need a good initial guess. While Ramalingam (2013), try to register points to plane by considering coplanar points in one dataset against their corresponding plane in the other dataset. Of course the problem of correspondence between coplanar points and plane has first to be solved. And here the constraint of the points being coplanar is used. And these methods have also the advantages of less iterations.

A reliable alternative may also be the plane to plane registration. Many researches have been carried out in this domain. Bosche (2012), proposed a registration method of 3D point cloud with 3D CAD model. The method was semi-automatic. The extraction of planes from the laser data was manual. Brenner and Dold (2007), showed an improved method for fully automatically registering laser scans. They extracted planar patches. To reduce the search space, the authors use hierarchical test combined to angular constraint.
The mathematical transformation model of plane to plane registration is completely described in Brenner and Dold (2007) and Jaw and Chuang (2008), but it has been well summarized by (Thapa, 2009), from which we give the major steps.

As expressed in Brenner et al. (2008) we need at least 3 pairs of non parallel planes represented by their normal and distance from origin. Considering the normal vectors (a,b,c,1) and their corresponding transformed counterparts, Jaw and Chuang (2008) elaborated the mathematical transformation as :

$$\begin{bmatrix} a_i^{1'} \\ b_i^{1'} \\ c_i^{1'} \\ d_i^{1'} \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} & 0 \\ m_{21} & m_{22} & m_{23} & 0 \\ m_{31} & m_{32} & m_{33} & 0 \\ -m_{41} & -m_{42} & -m_{43} & S \end{bmatrix} \begin{bmatrix} a_i^{1} \\ b_i^{1} \\ c_i^{1} \\ d_i^{1} \end{bmatrix}$$ Equation (1)

Where
$m_{41} = m_{11}\, T_X + m_{21}\, T_Y + m_{31}\, T_Z;$
$m_{42} = m_{12}\, T_X + m_{22}\, T_Y + m_{32}\, T_Z;$
$m_{43} = m_{13}\, T_X + m_{23}\, T_Y + m_{33}\, T_Z;$

$a_i^{1'}, b_i^{1'}, c_i^{1'}, d_i^{1'}$ is the normal vector of $(a_i^1, b_i^1, c_i^1, d_i^1)$ transformed system1 to system 2.
And the rotation matrix is considered as:

$$(R)= \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix}$$

(Jaw & Chuang, 2008; Thapa, 2009)

To compute the rotation parameters (ω,Φ,κ), Thapa (2009) divided the rotation matrix into its three components Rx, Ry, Rz before giving the values of m11 through m33 in terms of ω,Φ,κ as shown below:

$m_{11} = \cos(\kappa)\cos(\phi)$
$m_{12} = \sin(\varkappa)\cos(\omega) + \cos(\kappa)\sin(\phi)\sin(\omega)$

$m_{13} = \sin(\varkappa)\cos(\omega) - \cos(\kappa)\sin(\phi)\cos(\omega)$
$m_{21} = \sin(\kappa)\cos(\phi)$
$m_{22} = \cos(\varkappa)\cos(\omega) + \sin(\kappa)\sin(\phi)\sin(\omega)$
$m_{23} = \cos(\varkappa)\sin(\omega) + \sin(\kappa)\sin(\phi)\cos(\omega)$
$m_{31} = \sin(\phi)$
$m_{32} = -\cos(\phi)\cos(\omega)$
$m_{33} = \cos(\phi)\cos(\omega)$

So the rotation parameters will be
$\omega = \tan^{-1}(-m_{32}\ /m_{33})$
$\phi = \tan^{-1}(m_{31}\ /\sqrt{m_{32}^2 + m_{33}^2})$ Equation (2)
$\kappa = \tan^{-1}(-m_{21}\ /m_{11})$

(Thapa, 2009)

Once the rotation parameters obtained, the computation of the translation parameters was derived by Brenner et al. (2008) and confirmed by Thapa (2009) as

$T = (R^T R)^{-1}\, R^T\, m_4$ Equation (3) where m4 = $\begin{bmatrix} m_{41} \\ m_{42} \\ m_{43} \end{bmatrix}$

Refining the registration:

Generally, the estimation of these parameters: rotation, translation is approximate. This may be due to the presence of noise or inexact correspondences. And having more than the minimum 3 corresponding planes (redundancy measurements) may help reduce the errors (Thapa, 2009). As the number of planes increases, by mean of least –square adjustment, more accurate parameters and a fine registration are achieved. In order to have a more precise and fine registration, a process of progressively minimizing a distance function is started. This distance could be between corresponding points of the datasets or a point in one dataset and another in the other dataset or the distance between corresponding planes of the datasets (Salvi et al., 2007).

The working principle of least square adjustment has been also summarized by (Thapa, 2009) using corresponding points. However these equations were adapted and could be extended to corresponding planes from (Thapa, 2009) as follow:

- X_0 the initial solution of vector of unknowns. X_0 is the result of the transformation parameters computed from the coarse registration.
- V is the vector of residuals obtained after the first transformation of the two datasets using the transformation parameters of the coarse registration.
- ΔX is the vector of adjustments for the unknowns. ΔX is computed from the following equation:
-

$$\Delta X = (P^T\ IP)^{-1}P^T IV \qquad \text{Equation (4)}$$

Where P is the Jacobian matrix and defined as partial derivative of equation (1) with respect to every unknown.

I is the identity matrix.

Hence the newly computed solution X will be given by:

$$X = X_0 +\ \Delta X \qquad \text{Equation (5)}$$

The equation (5) is iterated until convergence. After each iteration, X_0 will be given the newly computed X. and X will be computed again.

2.3.4 The other methods used in registration of 3D Point cloud /3D CAD model:

Kim et al. (2010) have proposed a fully automatic registration method between 3D CAD model and laser point cloud obtained from construction site. The registration was done in two steps. A coarse registration using PCA (principal component analysis) and a fine registration. But before these two steps, the two datasets have undergone a processing step. The CAD model had to be converted into sterolithograpght (STL) format then transformed into points having same resolution the author called "uniform resolution points". To complete the pre-processing, the author put the two datasets in same resolution in a bid to improve the accuracy of the registration. For the fine resolution, Kim et al. (2010) used an improved version of ICP called Levenberg-Marquardt ICP (LM-ICP) in order to take care of the noise in the point cloud during the registration. Although, the registration was successful and automatic, the pre-processing helped the two datasets to have uniform resolution which may be robust in case of occlusions, its computation cost and efficiency which may be subjected to questions in case of "unordered" and complex large datasets which may be the case of big construction site. Furthermore the use of the PCA for the coarse registration imposed the datasets to meet predefined conditions. Kim et al. (2013) tried to use the fully automated method proposed by Kim et al. (2010) to perform an automatic 3D registration. However the extraction of feature from the laser scans data uses not only the coordinates of position of points (x, y, z) recorded with a laser scanner but also includes colour information (R, G, B) using a camera device. This make the process too complex, because the laser scanner and camera may not always be aligned but also complicate extra leaning colour algorithm was used. This method may also not work if both or one of the datasets has uniform colour as in case of a CAD model. During the phase of automatic registration, the presence of occluded data may, also be a challenge. Instead Golparvar-Fard et al. (2011) used point cloud from image dense matching in construction site monitoring by registration of 3D point cloud to a 3D/4D model by taking photographs from the ground. Then a closed-form method using unit quaternion was adapted to compute the transformation before registering the two datasets. The aim of these photographs taken from the ground was to avoid occlusions generally affecting traditional photogrammetric methods.

2.3.5 Conclusion of 3D/3D registration

Although registration is an important part in many applications, it automation for large scale applications is required for the purpose of achieving efficiency. When it is performed manually, it is vulnerable to human errors and subjective interpretations which may lead to inaccurate results (Kim et al., 2010).

From the methods of registration of point cloud and CAD model described in the literature review, we have globally two methods: the point to point registration and the feature based registration. With Point to point registration: the CAD model is converted into points to have both datasets in point format. Generally an ICP or improved ICP is used to perform the registration. Examples of these methods have been proposed by Besl and McKay (1992), Boulanger et al. (1996) and Boukebbab et al. (2007). However as stated by Kim et al. (2010), the original ICP considers most registered datasets to be characterized by outliers besides the problem of overlapping. The imaged-based point cloud of the data to be registered is noisy because of the dense matching. So this ICP cannot be used in its actual format. A flexible method which is more robust in noise correction has to be adapted.

According to Boulanger et al. (1996), points and lines are very sensitive to noise and clutters. The authors argued that the surfaces are less vulnerable to noise, and could be extracted. This was also confirmed earlier with a study by Marshall et al. (1991), where it was found that planes are more reliable than points for matching and also more robust to the presence of noise. Furthermore common planes are more distinguishable from different datasets than points (Bosche, 2012).

In this study our datasets as described in Section 3.1 are a building (made of planar structures) and an imaged based point cloud (noisy). So an appropriate method to register these two datasets may be the plane to plane registration.

3. METHODOLOGY

This chapter describes the methodology used. Section 3.1 gives an overview and description of existing types of segmentation algorithms and strategies; Section 3.2 described the methodology itself with the presentation of the global workflow, followed by the description of the different steps of the workflow: the features extraction, the matching strategy, and the type of registration performed.

3.1 Point cloud planar segmentation

To do a feature based registration, you need to extract features like points, lines, and planes. When there is presence of manmade objects like buildings, they are likely to be planar features (Vosselman, 2009). The most reliable features we can extract from buildings are planar features. With point cloud data of the building, we first need to perform segmentation by employing planar surface model. (Vosselman, 2009).
Segmentation could be defined as the process of identifying the measurement of each point within a point cloud so that to group points having same label into regions (Rabbani et al., 2006). There are many types of segmentation algorithms as listed and described in Rabbani et al. (2006) and Vosselman et al. (2004). These include edge based segmentation, surface based segmentation, and scan line based segmentation with strategies like top down, bottom up and global. For our case of the building point cloud data, we need to extract planar segments. Therefore an appropriate algorithm could be the surface base segmentation combine with the surface growing strategy (Pu & Vosselman, 2006).

The surface growing strategy is divided into two steps: the seed region selection and the region expansion (Brenner et al., 2008). To determine the seed, Brenner et al. (2008) selected plane characteristics like proximity of points; locally planar or smooth normal vector field could also be used (Vosselman et al., 2004).The other important part of the surface growing is the region expansion. The neighbouring points are added to the selected seed region (if they are within a specific threshold) and the plane equation is updated. This process need to be iterated until no point is below the set threshold. Its main steps is well described in Rabbani et al. (2006) and summarized by Brenner et al. (2008).

In conclusion, according to Brenner et al. (2008) and Grant et al. (2012) segmentation is still a large and extensive field of research, so we need to adapt it to the level of planar segmentation. The type of segmentation to be chosen may depend and take advantage on the fact that we may have enough information on the type of features which are expected to be available within the scene, or which are expected to be extracted (Böhm et al., 2000).

3.2 Methodology

3.2.1 Overview and flowchart

When feature based method is chosen for registration, two majors challenges should be addressed, i.e the correspondence and the transformation problems. These are closely linked to each other and the solution of one is determined by the other (Ramalingam & Taguchi, 2013; Schenk et al., 2000) .
The correspondence issue tries to find relation between features. Once this correspondence problem solved, transformation parameters are computed so that differences between the two datasets are progressively minimized (Schenk et al., 2000) . To overcome these problems, a general methodology has been proposed in Figure 3.1.

The methodology consists of mainly the following steps:

- The pre-processing and extraction of features which are mainly the segmentation of the UAV data and the extraction of planar features for both the UAV and CAD model datasets.
- The matching strategy to have a first estimate of corresponding features. As it will be elaborated in following sections, this part will use common geometrical characteristics of features and their relationship to have a first estimate of possible corresponding features.
- The refinement of the matching partners to more reliable matching corresponding features. the use of geometry or relation between primitives could lead to false correspondences, or one feature having more than one partner. A more restrictive strategy is needed to filter out the bad correspondences.
- The computation of the transformation parameters as described in Chapter 2 Section 2.3.3 before performing the registration,
- And finally the evaluation of the registration

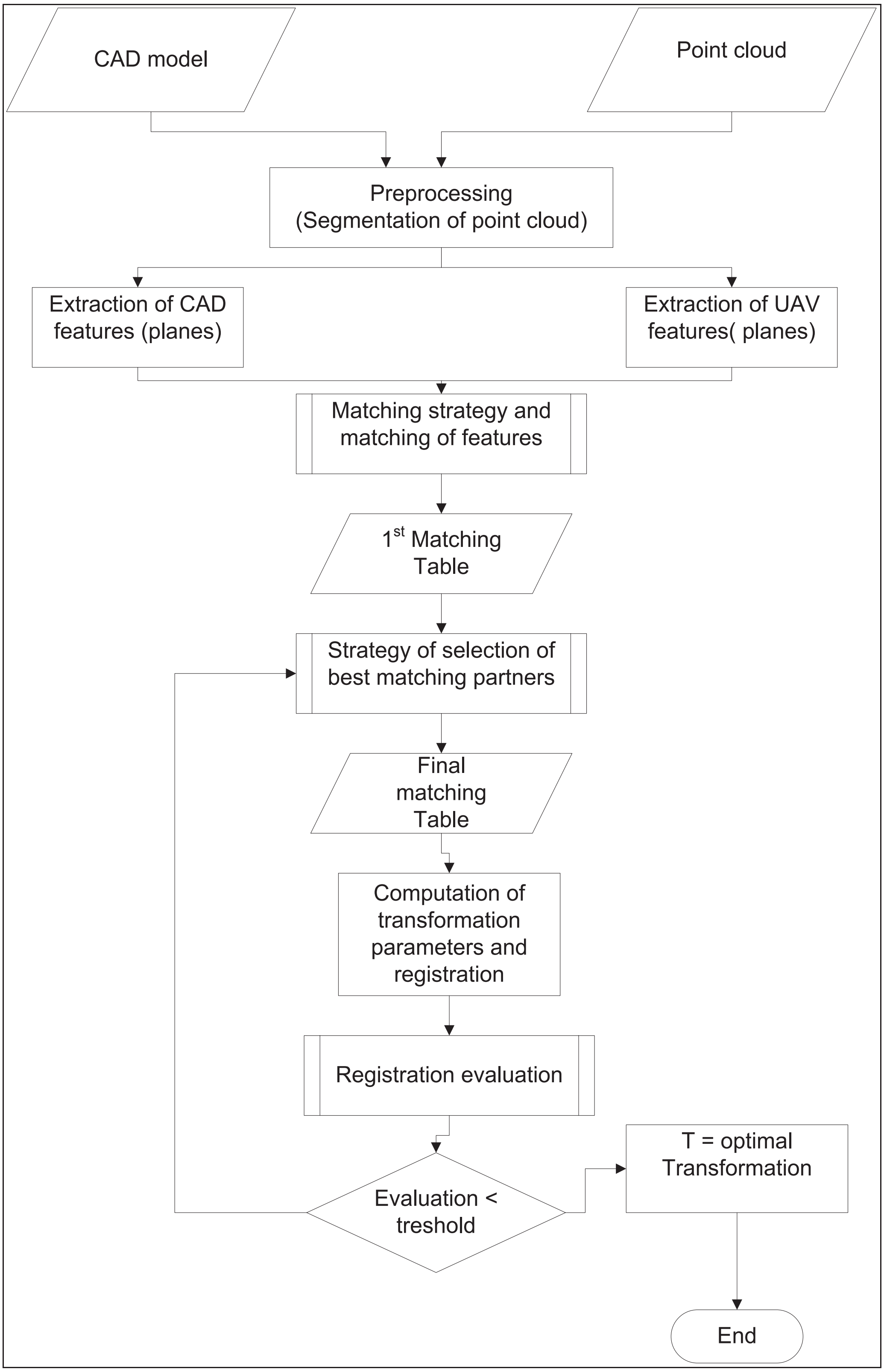


Figure 3.1: General methodology workflow

3.2.2 Features extraction

(a) Identification of f features

The extraction of features is very important. Because the result and accuracy of the registration depend closely on it. The consequence of choosing inappropriate features could lead to the overfit of the model (Kim et al., 2013) and hence bad result. The robust extraction of corresponding features is a big challenge in registration (Bosche, 2012). Many methods have been adopted for extraction and matching of features. We can distinguish point based, target based and feature based matching. In manual matching well distinguishable corresponding points are manually selected. While in target based matching prior manually placed targets into the scene are identified in both data. The manual method could be time consuming, difficult and many tasks could be repeated over and over again (Kim et al., 2013) . The feature based matching is aiming to be semi-automatic or fully automatic. But it has to overcome problems like lack of texture, self-similarities and occlusions (Bosche, 2012).

(b) Extractions of segment features from point cloud and CAD model

- **The point cloud:**

As stated when we have buildings, we need to extract planar features. For the Point cloud, we extracted features; specifically planes using segmentation (see Section 3.1). We adopt the planar segmentation strategy, a process by which points are in a same plane are identified and grouped together (Wang, 2013) . Despite many attempts to solve it, a recurrent problem with image based point cloud is its noise level, especially when a dense stereo method has been applied. This is due to the type of matching applied within this technique. This results specially in noisy flat surfaces (Gerke, 2009; Musialski et al., 2013). Since surface based segmentation combined with surface normal estimation is less sensitive to noise (Rabbani et al., 2006), we could use the strategy of surface growing as described in Section 3.1.

- **Extraction of segment features:**

After the segmentation, the next step is the extraction of the segment features. A dense point cloud is a set of 3D points with known coordinates (Wang, 2013), therefore to extract planar features we just need to group the points of coordinates (x, y, z) having the same segment number with the help of a software like matlab.

- **The CAD model:**

For the CAD model, the procedures (plane fitting of RANSAC, computation of plane parameters) as for the point cloud were applied (see Section 4.4), except for the extraction of the CAD planes. To extract the CAD planes, an xml file generated from the RZI file or an obj file of the model from Imagemodeller were used and the matlab software to read the coordinates and plane number. After the fitting of a plane, the same parameters information as in the case of the point cloud were computed.

3.2.3 Matching and strategy of search

(a) Matching features

For estimating the rigid transformation parameters (rotation + translation) we need at least two non-parallel matched pairs of planes for the rotation and three non-parallel matched pairs for the translation estimation (Bosche, 2012; Marshall et al., 1991). But for the optimization of the least square adjustment more planes should be used (Marshall et al., 1991) . Bosche (2012), added that to have better result, the features to be matched should be spread in space as much as possible. After choosing at least 3 non parallel planes, the order in which matching pairs are taken may also influence the speed and accuracy of the transformation result estimation (Marshall et al., 1991) . To choose the best possible matching pair to get better result, Marshall et al. (1991), proposes the following rules: largest area first, when there is planar, cylindrical and spherical faces, choose simpler before complex one and at last the faces with more neighbouring faces should be chosen first.

(b) Possible constraints to be used during matching

Matching is the process of finding a common feature in two or more datasets. Although finding corresponding primitives depends on the actual datasets to be aligned, often the problem of matching between two 3D datasets could be summarised as an assessment of the quality of primitives or planes to be matched. This assessment include generally three steps: the common geometrical characteristics of the two primitives to match, the similarity of relationship of primitives in one dataset with that of primitives in the other dataset and finally to grade negatively primitives with no correspondence in either dataset to eliminate them (Zhang, 1993).

If we want to use area of planar faces for matching, only planes that are likely to be equal in area may be matched. Because noise areas of scene and model planes cannot be exactly equal, the matching of scene plane which is greater than model plane is ruled out (Marshall et al., 1991). Marshall et al. (1991) further stated that segmentation of curved surface may generate very small planes, and using these small planes during matching may generate considerable errors; hence, to avoid these errors a threshold may be set about minimum size of a plane to be matched. This will help to identify and reject these small planes. Furthermore, when reliable planes and noisy planes are clearly identifiable, it is better to choose first the reliable ones for matching before considering the noisy planes. Because noisy planes could increase the search time and add errors to the estimation of the transformation (Marshall et al., 1991). According to Boulanger et al. (1996), for matching surfaces, we have two methods: the use of quaternion to estimate the rotation, or the use of centres of gravity of surfaces. But the centre of gravity method is very sensitive to occlusions and does not offer any constrain which could be used during matching.

Considering all the constraints and possible methods described above and the process of finding corresponding planes; we have used the method proposed by Li et al. (2013), which may be integrated with methods used by Monnier et al. (2013), and Brenner et al. (2008). Furthermore, to limit the search we added some constraints by the use of heuristics to give priority to correspondences base on parameters like size or number of points (Rabbani & van den Heuvel, 2005). Combining these methods, we have the following steps:

We compute for each plane in both datasets for following parameters:

- Selection of big-sized planes (extraction of planes of larger size)

Since the dimensions of the building are around 5 m. We could consider a segment having a length equal or greater than 2m or a width equal or greater than 2m as a big-sized plane.

So to select large planes we perform the following steps

a. We compute the length of the plane L =max(x) – min(x)
b. We compute the width of the plane W =max(y) – min(y)
c. For selecting the big-sized planes we put a threshold by stating that a plane is considered to be a large one if t L > =2m or W>=2m.

- Computation of m:n matches (1 to many correspondences) using compatibility of normals between potential corresponding planes
- Computation of m:n matches (1 to many correspondences) using minimum distances (closeness) of potential corresponding planes.
- Consider both properties for the computation of the first estimate of possible matching corresponding planes (m:n correspondences)

This is summarized in Figure 3.2.

In our first estimate matching table we have n:m correspondences which means that each feature in one dataset corresponds to n features in the other dataset and vice versa. This choice is motivated by the fact that the Euclidian distance and the angle difference may change in presence of noise (Dubuisson & Jain, 1994). So the matching was done to consider in the first stage all possible candidates which may correspond to a particular feature. However, it is necessary to filter out false correspondences. Because the presence of false correspondences may affect our registration result (Zhang, 1994).

To select best correspondences, a direct "brute force" may be a solution, i.e. computing and testing every possible combinations (Khoshelham, 2010). Its main disadvantage is that it is computationally expensive. Khoshelham (2010), estimated the number of combinations for two sets of m,n planes where K corresponding pairs are needed for registration as:

$$n_c = C_k^m \bullet P_k^n = \frac{m!}{k!(m-k)!} \times \frac{n!}{(n-k)!} \quad \text{Equation (6)}$$

Where C and P denote combination (unordered selection), and permutation (ordered selection) respectively.

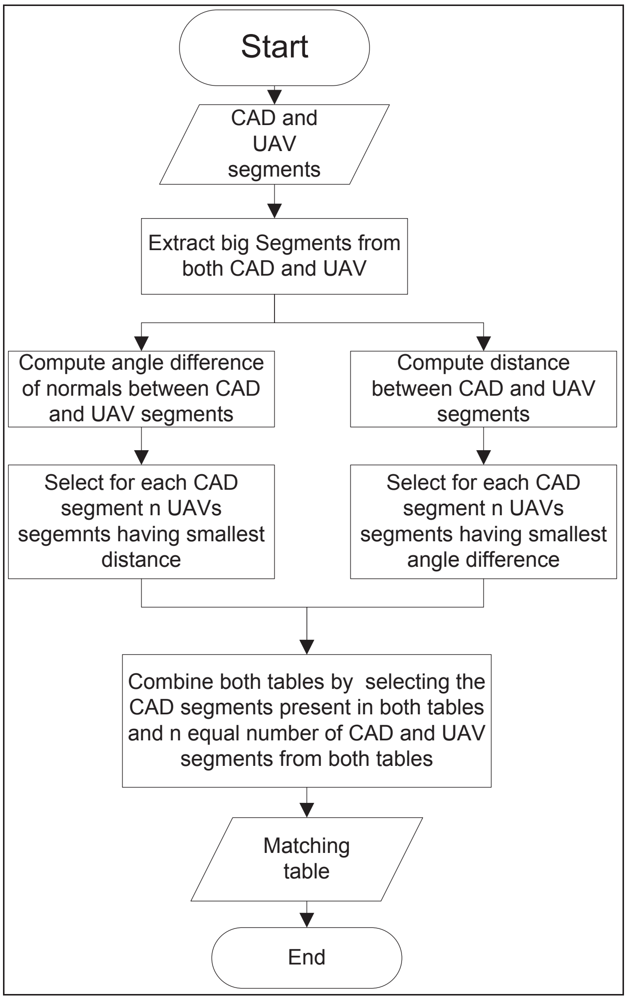


Figure 3.2: Matching strategy for first estimation of corresponding planes

(c) The matching strategy:

After extraction of planes, we should look for corresponding planes by matching. To establish the correspondences, following plane features like area, , size, plane–plane distance, plane angle among others, could be used (Brenner et al., 2008; Li et al., 2013; Rottensteiner, 2002). But not all of these characteristics are compulsory to consider. Some of them may not be reliable due mainly to occlusions or clutters which may be responsible of different values for the same feature (Brenner et al., 2008).
In our case, the two datasets are close to each other (coarse registration), this means corresponding planes should be close to parallel (Li et al., 2013) . The same idea is also used by Brenner et al. (2008). They consider two planes match if they have similar directions of normals and distances from origin. Therefore, we could use the compatibility of normals, and closeness (distance) properties to find corresponding planes between our two datasets. To achieve this, following steps adapted from Li et al. (2013) were used:

a. Computation of angle difference between normals of all CAD planes and UAV planes. We then set a threshold to select the pairs of UAV and CAD planes having smallest angular difference as potential corresponding plane candidates. This will lead to m:n correspondences. Which means that a CAD plane can have more than one corresponding UAV planes and vice versa.
b. Computation of the distances between all CAD and UAV planes. And same as in the case of the angle difference, we then set a threshold to select the pairs of UAV and CAD planes having

smallest distance (which are close) as potential corresponding plane candidates. This will also lead to m:n correspondences.

c. Combination of the two to derive the first estimate of possible corresponding planes matching table. Later an algorithm will be used to refine the matching table.

To compute the distance between each plane of the CAD model and each plane in UAV point cloud, we could use the distance between normal and centre of gravity of planes or the distance between centre of gravity of the planes. Here we have chosen the distance between the centres of gravity, because even though the centre of gravity may be disturb by occlusions or noise(Boulanger et al., 1996) it is more stable than the normal of the plane which is not fix.

(d) Strategy of selecting best matching partners

The first estimate matching table may result in many corresponding pairs which are not necessarily correct. False correspondences need to be removed.
To reduce the number of combinations and limit the search complexity, Khoshelham (2010) used the "INITIATE-AND-EXTEND SEARCH" while Rabbani and van den Heuvel (2005) used a strategy called "constraint propagation".
If some have been successfully implemented, the risk of suppressing good matches has always been present, and generally the techniques need to be adapted with the type of data we have (Brenner et al., 2008).

Taking into account the above analysis, the characteristics of our datasets (see Chapter 4, Section 4.1) , and knowing that to compute transformation parameters we need at least 3 non parallel corresponding planes, we choose the option to compute all possible combinations of 3 non parallel corresponding pairs. The next stage is the testing of each to identify good combinations. The summarize steps are shown in Figure 3.3.

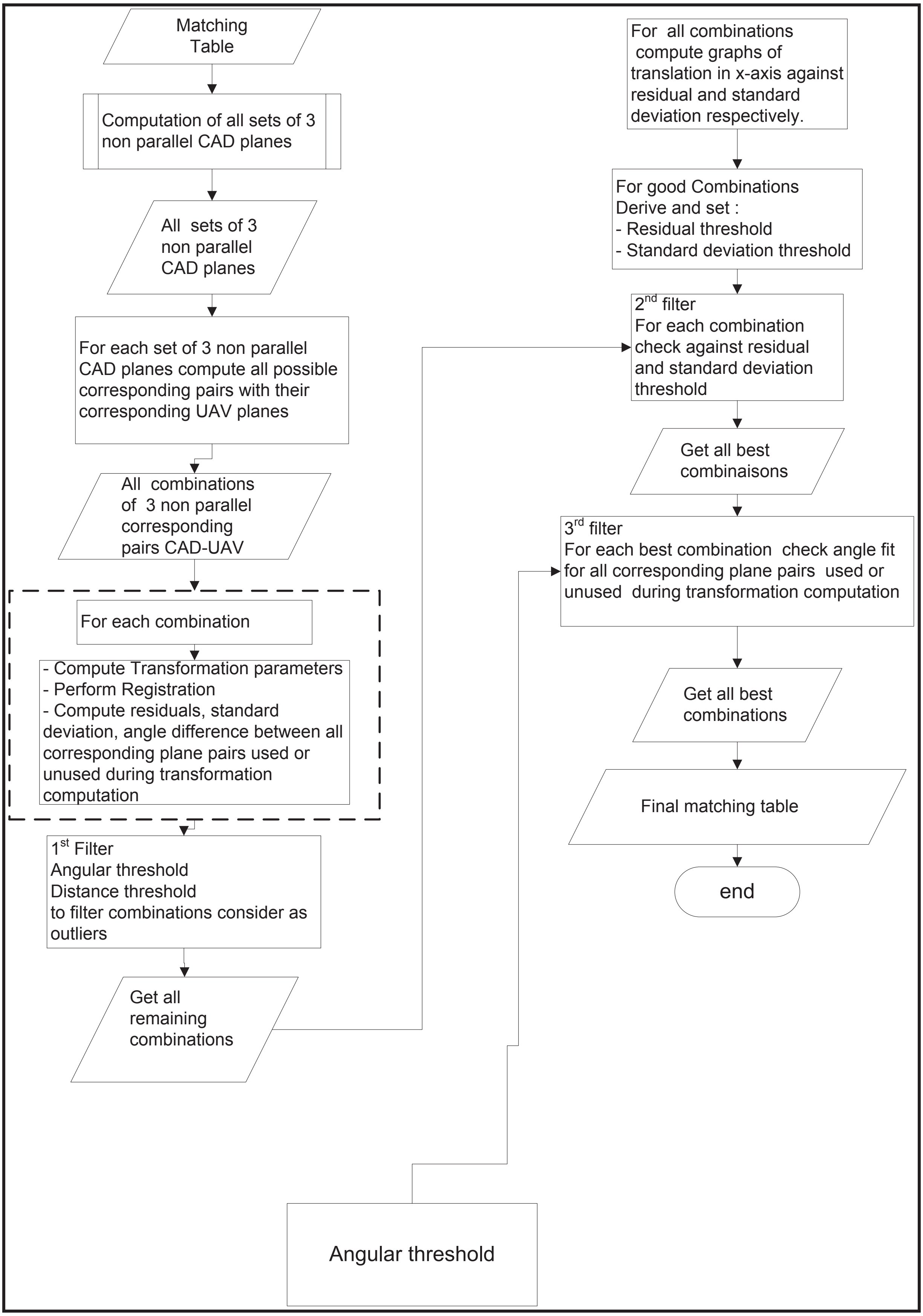


Figure 3.3: Strategy of selecting final matching table

The first step is the computation of all possible combinations of three (3) non parallel pairs taking the first estimate matching table as input. Three examples of such combinations are shown below in Table 3.1.

CAD	UAV
11	93
31	1
71	172

CAD	UAV
11	93
31	1
71	135

CAD	UAV
11	93
31	52
71	172

Table 3.1: Examples of possible combinations of 3 non parallel corresponding pairs (numbers given are segments Ids)

To reduce the number of combinations, and avoid errors during the computation of the transformation parameters, we need to remove false correspondences by applying a modified version of method proposed by Zhang (1994). To put in place a robust method, Zhang (1994), used a statistical method of which the main idea is that points belonging to same frame (plane) should have approximately same residuals, if the registration is good. Zhang (1994), sets two parameters: A distance D (residual) to indicate when the registration is good and the maximum distance D_{max}, which is the tolerable distance (residual) where the registration is still acceptable.

Our method is based on the geometrical relationship of corresponding planes after registration. Two parameters are taken into account: the Residuals threshold and angle differences between corresponding planes.

- Residual threshold: after registration we need a maximum distance between each CAD plane and its transformed corresponding UAV plane (threshold) above which the matching is considered bad, since we consider the datasets are close before registration.
- The angle difference between corresponding planes (referring to the initial condition of the data before registration) should not exceed a certain threshold after registration.

To make sure that these geometrical relationships between corresponding planes after registration are maintained and at the same time allowing us to identify and remove bad correspondences, three filters were used. Each filter has a specific threshold to progressively filter out the false correspondences.

- The first filter is the angular threshold and residual threshold above which, a combination could be considered just as an outlier, because the registration of these combinations results in large residual values and angle differences between "corresponding planes". To set these thresholds, we can consider the initial condition of the datasets before registration.
- For the second filter, it is based on the rule that combinations which result in good registration result should be having same transformation parameters (translation and rotation) (Zhang, 1994). So we are going to set two thresholds:
    - A maximum distance D_{max}, which is the tolerable distance (residual) where the registration is still acceptable.
    - A maximum standard deviation which is the tolerable value where the registration is still acceptable.

To set the thresholds for the residual and the standard deviation, we can plot a graph of translation in x-axis against residuals in y-axis on the one hand; and the graph of translation in x-axis against standard deviation in y-axis of all combinations on the other hand. By identifying the location of accumulation of some combinations, we will be able to give an estimation of these thresholds. An example of this kind of graphs is shown in Figure 3.4. The accumulation of combination is clearly distinguishable around zero of the x-axis.

- 3rd filter: The goodness of selected combination from filter 2 (with corresponding parallel planes after transformation) is checked using the 3rd filter. The purpose is to investigate that the selection from filter 2 was reliable and also removed bad combination which may not be detected from these thresholds due to errors in their estimation.

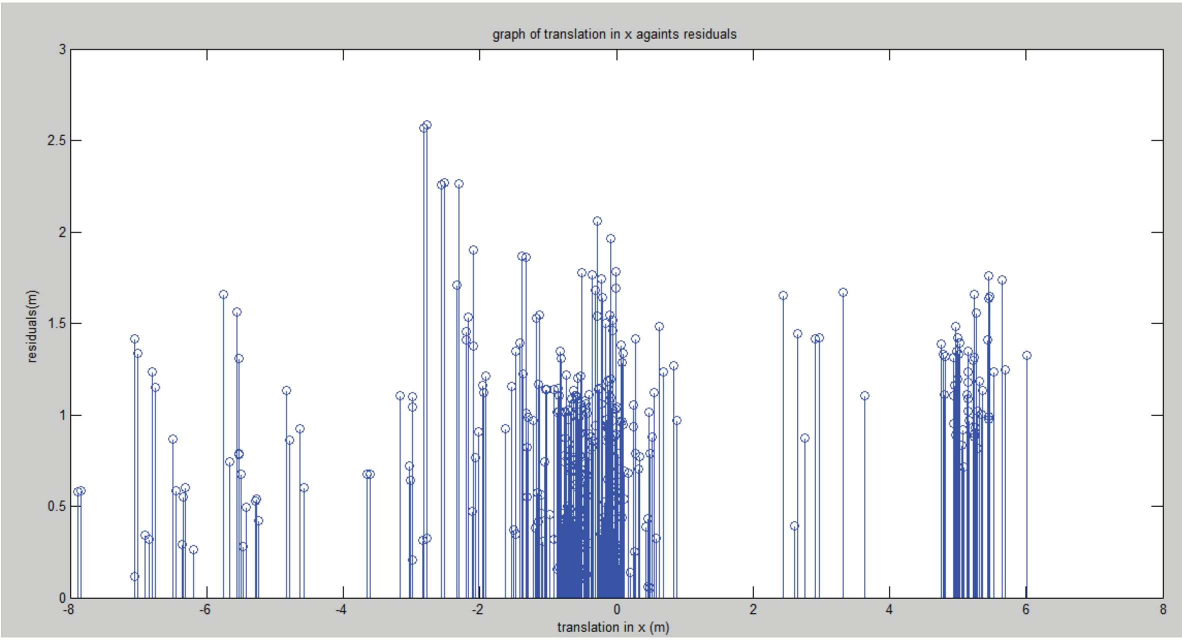


Figure 3.4: Graph of translation in x-axis against residuals

3.2.4 Estimation of transformation parameters using least square Adjustment or fine registration

The grouping of all final good selected combinations together will result in having more than 3 corresponding pairs. Having more than 3 corresponding pairs (redundancy), a least square adjustment (see Chapter 2 Section 2.3.3) could be applied for the registration of the two datasets to have better results.

4. IMPLEMENTATION RESULTS AND EVALUATION

This chapter presents the implementation results of our methodology. Section 4.1 describes the datasets. Section 4.2 shows result of pre-processing of datasets. Section 4.3 presents the extracted features followed by the description of the computation of segment parameters in Section 4.4. The results of the matching and the registration are described in Section 4.5 and 4.6 respectively.

4.1 Description of the datasets

The two datasets to register are from the same object. They are represented by a CAD model and a point cloud. These two datasets even though they are from the same set of images, they have been created by two completely independent processes. The point cloud was generated from a set of images taken from different viewpoints. First the software 123D Catch was used to do the orientation of the images. This software is able to do the orientation automatically using an algorithm called Structure From Motion (SFM). SFM uses corresponding points in two or more successive images in order to reconstruct the 3D object structure as well as the camera motion and orientation. In a second phase, the Patch Based Multi-View Stereo (PMVS) technique was used to have the dense point cloud. The Figure 4.1 shows the raw point cloud obtained from SFM and PMVS.

As shown the building is surrounded by trees and vegetation which may come as occlusions in case of segmentation. The door is opened; this also may give inconsistent planar structures which may be used as a simulation of a damage situation in case of damage assessment of a building.

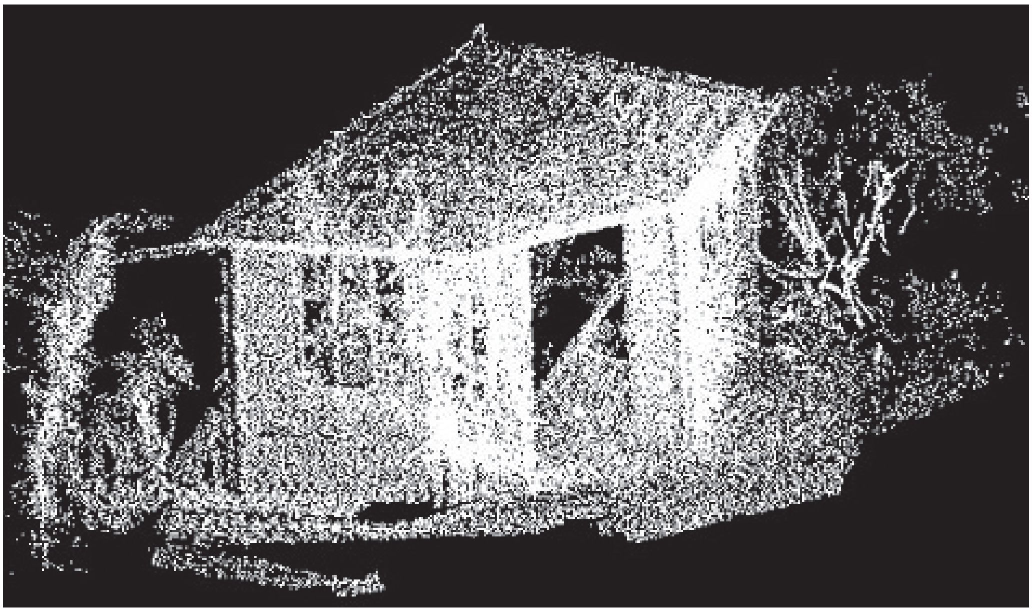


Figure 4.1: Raw data point cloud

The CAD model was obtained using Image modeller software .This software is used to create 3D models from images. The same set of images was loaded into the software before manually modelling the object. But prior to this the software 123D Catch was chosen to do the orientation of the images automatically. During the modelling of the CAD model a wrong CAD plane has been assigned on purpose for simulation. This will help us to analyse how our registration algorithm will behave in case of a CAD plane without corresponding UAV plane. Furthermore, in a real situation, it can be the case of a wall which was part of the building and for some reasons was removed or destroyed. In the discussion we will analyse the effects of this CAD plane in the overall registration and generalise with a conclusion. After the modelling, the model is exported to software like AutoCAD to generate the full 3D CAD model. The 3D CAD model is shown in Figure 4.2.

As in most CAD model, we have geometrical structures like rectangle, triangle, square, among others. The geometrical structures are slightly tilted, and as visible in Figure 4.2; we don't have perfect match at the intersection of the geometrical structures. This may be due to errors as a result of the manual modelling of the structures. These errors may come also from the manual definition of the World Coordinate System and reference distance (scale) during the orientation of the images using the 123D catch software. These errors will not only affect the quality of the CAD model, but also the result of the registration. In the discussion section, we will talk about the consequences of inappropriate or bad CAD model in the result of the overall registration between the Point cloud and the CAD model.

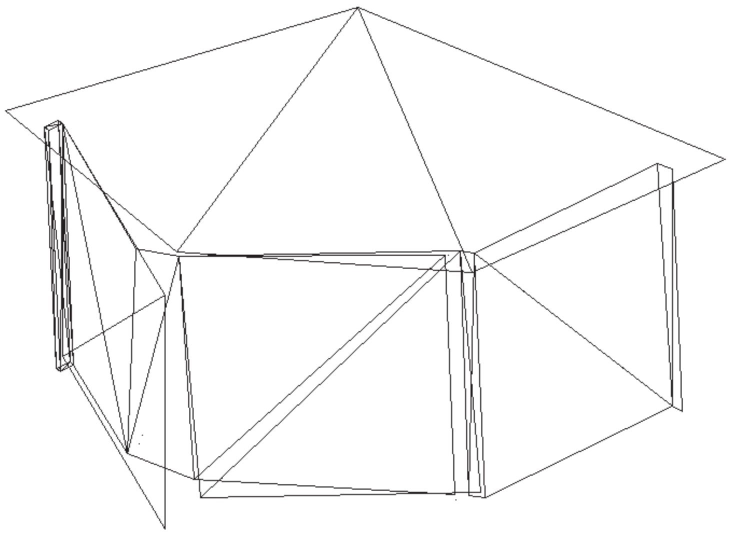


Figure 4.2: 3D CAD model

Since the processes of creation of these two datasets are completely independent, the errors generated while performing a dense matching and errors from image modeller are different in term of type and quantity. This will result in some offset or discrepancies between the CAD model and the point cloud in their initial states.

4.2 Preprocessing of the data

The pre-processing of point cloud was mainly the segmentation. Segmentation was performed using the Point Cloud Mapper (PCM) software. The strategy of surface growing with direct neighbours and planar surface model as elaborated in Section 3.1 was adopted. The following parameters were selected: the maximum distance to surface model parameter was set at 0.3 m. This distance was set according to the amount of noise expected with the data as we already described, imaged based point cloud are noisy. The surface growing radius is fixed at 0.3m while the minimum number of points is at 500 taking into account the high density of imaged based point cloud and the fact that in case of buildings we generally have large planar segments.

The process can be summarized in two steps:

- Segmentation of UAV data through PCM
- Generation of point coordinates and segment numbers before saving them in a txt file.

The result of the segmentation is shown in Figure 4.3. If we perform a visual inspection, we can notice that the different segments are clearly distinguishable. They can be differentiated by colour. The shape and size of some segments which are manmade planar structures like wall, door, roof, windows among others are also clearly identifiable. Very small structures with no clearly defined geometry are also visible.

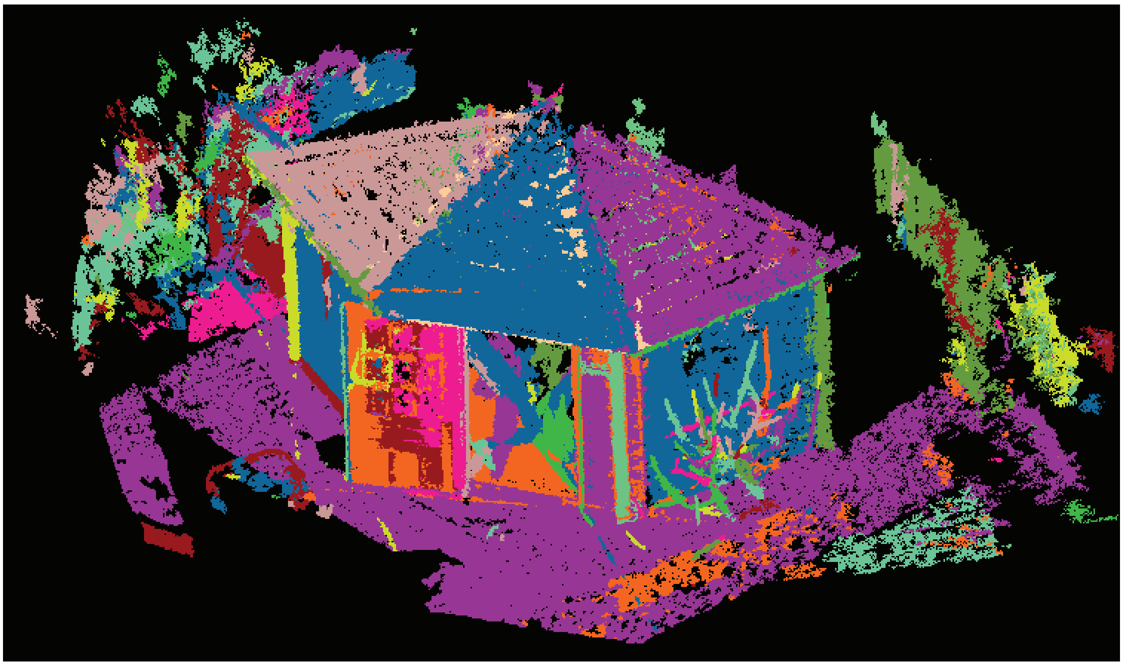


Figure 4.3: Point cloud after segmentation.

4.3 Extraction of features

- **Point cloud**

As described in Section 3.2.2, the extraction of planar features from the point cloud (after segmentation); was done by the grouping and extraction of points with common segment number. The software matlab version R2013a was used to compute plane parameters. The Figure 4.4 below shows examples of the extracted segments. As it can be noticed, there are well structured planes, there are also unstructured segments. The well structured segments could be explained by the presence of manmade structures in almost all buildings. But some segments were unstructured. This also could be expected because of the presence of vegetation and trees in the original point cloud, and the strategy of segmentation used.

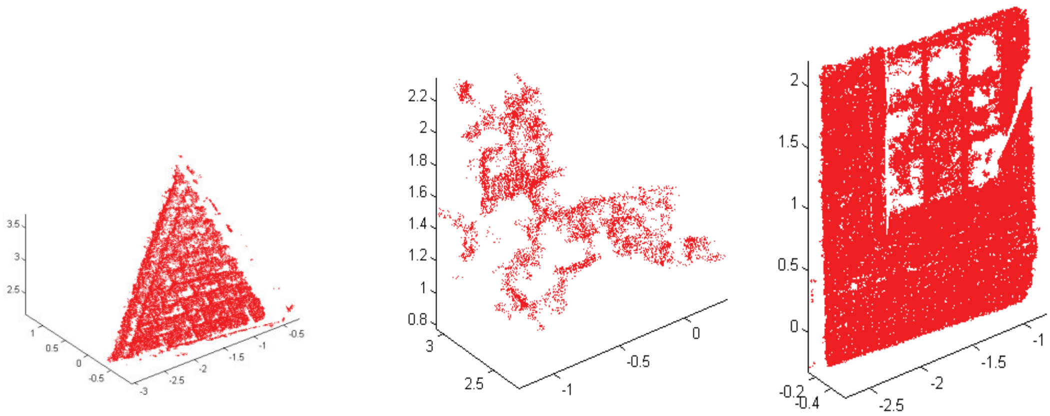


Figure 4.4: Examples of extracted segments from Point cloud

- **CAD model**

For the CAD model the following steps were used:

- Read the XML file from RZI file and the obj file from imagemodeller.
- Extract the coordinates of points of planes in a txt file
- Use of Matlab for the computation of plane parameters of CAD model after grouping the points with common point number

For the CAD model, planes are regular geometrical structures like rectangle, triangle, and square as in most CAD model. For our CAD model the geometrical figures are slightly tilted as stated before.

4.4 Computation of segment parameters

After extracting all segment features, we need to compute the parameters of each segment. Geometrically a plane is defined by its Hesse form, which mean its normal and the distance from origin (Rabbani & van den Heuvel, 2005) . As described in Chapter 2 Section 2.3.3, when computing the transformation parameters in a plane based registration, we need as input the normal and distance from origin (Brenner & Dold, 2007).
The plane parameters could be estimated using Principal Components Analysis (PCA), where the plane normal and the distance from origin are obtained respectively from the eigen-vectors with smallest eigen value and the median of the dot product between vector of each individual point and normal vector (Sande et al., 2010). And finally to remove outliers the plane fitting algorithm RANSAC is robustly applied to each segment (Sande et al., 2010). The plane P and its parameters adapted from (Sande et al., 2010) is shown in equation (7):

P= $(a, b, c, -d)^T$ (1) Equation (7)

Where the normal n=$(a, b, c)^T$ and d is the distance from origin

The others plane parameters like center of gravity or size may be helpful specially in the matching process, and may be tools which can be used in the result assessment. All the parameters computed are listed below.

- Normal
- d (distance from origin)

- Center of gravity
- Number of points (Size Segment)
- Minimum x, maximum x
- Minimum y, maximum y

4.5 Matching result

The extracted planes from both the point cloud and the CAD model will serve as our input for our matching process algorithm. But for the reasons elaborated in Chapter 3 Section 3.2.3 only large size planes from both datasets are selected. If we consider the number of correct and reliable CAD planes (eight) at the beginning only five were appropriate (see Chapter 3 Section 3.2.2). For the UAV, out of a total number of 315 segments only 73 were selected. As an example, the result of selected large CAD planes is shown in Table 4.1.

CAD Plane Segment number	11	21	31	51	71
Width of CAD plane (m)	2.619	2.253	2.254	1.179	2.033
Length of CAD plane (m)	2.602	2.171	2.579	2.416	0.362

Table 4.1: Selected CAD planes.

To compute the transformation parameters we need a minimum of three (3) non parallel pairs. From these selected CAD planes, we tested all the combinations of possible sets of three (3) CAD planes. Only non-parallel triplets were finally considered.

As elaborated Chapter 3 Section 3.2.3, distance and angle constraints are combined to compute the first estimate matching table. Later wrong matched pairs were removed using the strategy described in Figure 3.3 of Chapter 3 Section 3.2.3 to make sure that only correct CAD-UAV pairs are matched. The result of the final matching planes of the two datasets is shown in Table 4.2. This table shows the segment numbers of computed corresponding pairs UAV-CAD model planes.

To check the accuracy of the matching, we compute the residuals and standard deviations for all final selected matched pairs. The residual is the mean distance between all points of a UAV plane and its corresponding CAD plane. The standard deviation shows variability from this mean. The result shown in Table 4.3 is the average residual, average standard deviation and angle difference of each corresponding pair from all good combinations of 3 non parallel corresponding pairs. Globally this average residual is low. This also confirms by the low standard deviation and angle difference. This implies that the matched planes are globally correct.

CAD plane segment number	UAV Plane segment number
11	93
21	113
31	1
71	135
21	315

Table 4.2: Result of final matching table.

Corresponding pairs Segment numbers		Residual (m)	Std (m)	Angle difference (degree)
11	93	0.022	0.013	0.985
21	113	0.033	0.013	0.923
21	315	0.039	0.023	1.047
31	1	0.030	0.014	1.417
71	135	0.054	0.022	1.518

Table 4.3: Average residual, average standard deviation, average angle difference of corresponding pairs CAD-UAV of final matching table

The Figure 4.5 displays the figures of two examples of corresponding matched segments. From visual analysis, the result of accuracy check is confirmed; the matched pairs seem to have approximately same shape, and orientation. In some cases the sizes are approximately similar as it was expected.

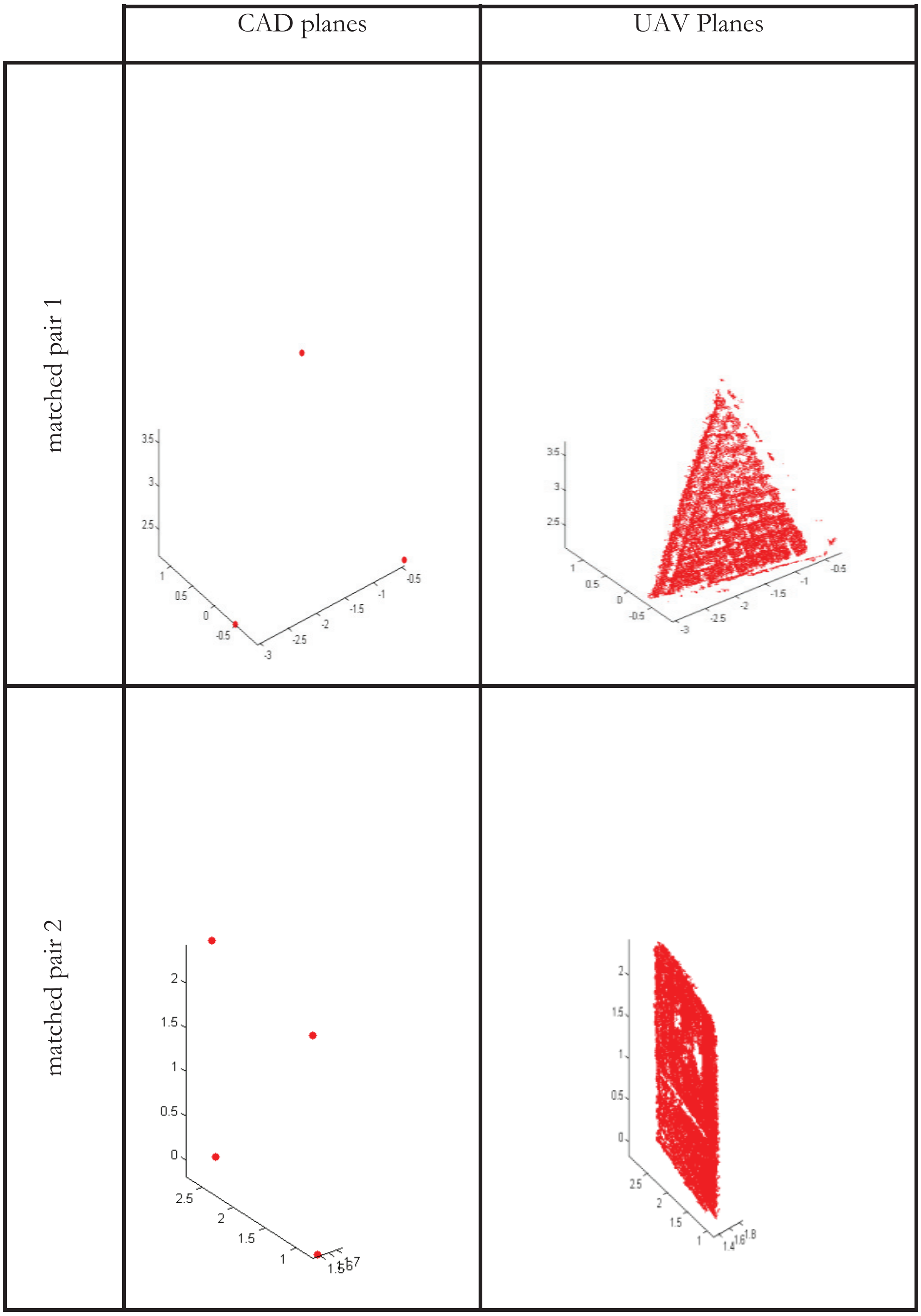


Figure 4.5: Examples of planes of final matching table.

4.6 Registration results

The final step is the registration of the two datasets. All correct matched pairs i.e five in number are combined. This can help to have more than 3 pairs of corresponding planes (redundancy) to be able to apply a least square adjustment. In a 3D similarity transformation, the CAD model was considered as the reference dataset and the UAV as the dataset transformed and registered to the reference dataset.

Table 4.4 shows the result of the 6 transformation parameters obtained. While table 4.5 displays the accuracy of the registration by showing the residuals (mean distance) between points of each UAV plane to the corresponding CAD plane and their standard deviation. The registration is correct with globally residual of less than 7cm and standard deviation of less than 3cm.

Rotation (degree)			Translation (m)		
Omega	PHI	kappa	Tx	Ty	Tz
-0.080	0.395	-1.264	-0.120	0.200	0.112

Table 4.4: Result of six transformation parameters: 3 rotation angles, 3 translations.

Corresp. Pairs ID	11 - 93	21 - 113	21 - 315	31 - 1	71 - 135
Mean residual (m)	0.014	0.037	0.033	0.036	0.068
Standard deviation (m)	0.010	0.014	0.023	0.019	0.026

Table 4.5: Result of mean residual (mean distance) and mean standard deviation between points of each UAV plane and the corresponding CAD plane and their standard deviation after registration.

5. ACCURACY ASSESSMENT AND DISCUSSION

This chapter is dedicated to the assessment and discussion of the results obtained in Chapter 4. It outlines matching strategy evaluation and registration accuracy in Section 5.1 and Section 5.2 respectively. Each section is concluded with a discussion about the results of the assessment and implementation.

5.1 Evaluation of the matching result

The correctness of matched features in feature based registration is critical in order to have good registration result. In this section we are going to do the evaluation of the matching algorithm. To do the evaluation we assess the quality of our matching algorithm qualitatively and quantitatively (Boudet, 2007). This will be done by comparing a computed dataset and a reference dataset: the matching result with the reference matching table. Both are presented as tables.
The evaluation technique used is adapted and well described from Khoshelham et al. (2010) and Rutzinger et al. (2009) . The comparison will allow us to identify corresponding matched pairs which are in both matching tables i.e the result and the reference tables. And the ones which are in either matching table or reference matching table and not present in the other table. The following classes are defined:

- The matched pairs which are both present in the two tables (result and reference) are considered correct or "classified": as true positive (TP).
- The matched pairs which are in result table and not present in the reference table are considered incorrect or "classified" as false positive (FP).
- The matched pairs which are in reference and present in another table (not the result table) are considered incorrect or "classified" as false negative (FN).
- The matched pairs which are in the reference table and not present in the result table are considered incorrect or "classified: as Unclassified positive (UP).

(Khoshelham et al., 2010; Rutzinger et al., 2009)

From these classes, the completeness is defined as the percentage of matched pairs in the reference table which are detected (detection rate). The correctness gives how the correct matched pairs are close to the reference. The quality link the two entities (Rutzinger et al., 2009). Here in our case the unclassified positive (UP) is the equivalent of false negative or FP. Equation (8), equation (9), and equation (10) were adapted from Rutzinger et al. (2009) to represent the mathematical formulas of completeness, correctness, and quality respectively.

$$\text{Completeness} = \frac{\|\text{TP}\|}{\|\text{TP}\| + \|\text{FN}\|} \qquad \text{Equation (8)}$$

$$\text{Correctness} = \frac{\|\text{TP}\|}{\|\text{TP}\| + \|\text{FP}\|} \qquad \text{Equation (9)}$$

$$\text{Quality} = \frac{\|\text{TP}\|}{\|\text{TP}\| + \|\text{FP}\| + \|\text{FN}\|} \qquad \text{Equation (10)}$$

To do the test, we manually edited the reference matching table. This is shown in Table 5.1. As elaborated before the CAD plane 51 is unassigned (has no matching partner).
We have tried to oversee the behaviour of the matching algorithm when it is subjected to different types of inputs like:

- Changing the initial position of the datasets: translation by 2 meters or rotation by 5 degrees
- Changing of the number of input planes by removing or adding planes.

What will be the variability of the result of the matching regarding these changes?
The result of the matches will be compared to the reference matching table which is holding the correct corresponding matched pairs. The reference matching table is shown in Table 5.1.

CAD planes	UAV Planes
11	93
21	113
21	315
31	1
51	unassigned
71	135

Table 5. 1: Reference Matching Table (manually edited)

For each of the different inputs described above, the following information will be computed

- Nature of inputs
- Reference matching table (does not change)
- 1st matching table (First estimate matching table)
- Final matching table
- Evaluation result.

5.1.1 1st test: Input n:m matches (1 to n correspondences)

In this test, for each CAD plane, four corresponding UAV planes were selected based on distance and angle as described in Section 3.2.3. The result of this selection is shown in Table 5.3 (b). Table 5.3 (c) displays the result of the automatically selected CAD-UAV planes: the final matching table of the matching algorithm. Its performance is in Table 5.3 obtained by comparing the reference matching Table 5.2 (a) and the finale matching Table 5.2 (c).

Reference matching Table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1
51	unassigned
71	135

a)

1st Matching table				
CAD planes	UAV planes			
11	93	138	93	85
21	113	315	113	315
31	1	52	1	70
51	3	4	116	152
71	172	135	135	168

b)

Final matching table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1
71	135

c)

Table 5. 2 Results of input n:m matches

TP	FN	FP	Completeness	Correctness
5	1	0	0.8	1

Table 5. 3 Evaluation Result

The correctness is 100% and the completeness is also high. Here all the matched pairs detected by the algorithm are in the reference table. But not all the matched pairs in the reference table have been detected. That is why the completeness is 80%

5.1.2 2nd test Removing CAD plane 11

In this test, we want to see the behaviour of our matching algorithm when a CAD plane is removed. For example, the CAD plane with segment number 11 was removed. The result of the first estimate matching table is displayed in Table 5.4 (b). We can notice that the CAD plane 11 is not present among the selected CAD planes with corresponding UAV. The final matching Table 5.4 (c) has no input which means that no corresponding CAD-UAV planes automatically selected by the matching algorithm

Reference matching Table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1
51	unassigned
71	135

a)

1st Matching table				
CAD planes	UAV planes			
21	113	315	113	315
31	1	52	1	70
51	3	4	116	152
71	172	135	135	168

b)

Final matching table
(no final inputs)

c)

Table 5. 4: Results removing CAD plane 11

Evaluation Result:

Here we have no correct combination.

This was expected, because the only correct combination comparing the 1st matching table to the reference table is 21 31 71 and this combination is not a non parallel one.
Here also the algorithm is performing well.

5.1.3 3rd test Removing CAD plane 71

To confirm the result obtained in test 2, that when a plane is removed, the matching algorithm is performing well. We remove another plane. The CAD plane segment number 71 and add again the CAD plane 11. The result of the first estimate matching table is displayed in Table 5.5 (b). We can notice that the CAD plane 11 is again among the automatically matched plane while it is not the case for the CAD plane 71. The final matching Table 5.5 (c) display the final corresponding planes selected. In this case, we have corresponding pairs confirming that our first test was correct. The absence of corresponding pairs in the second test were not due to failure of our matching algorithm, but effectively there was no correct corresponding pair available. The performance of the matching algorithm is in Table 5.6 also obtained by comparing the reference Table 5.5 (a) reference table and the finale matching Table 5.5 (c).

Reference matching Table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1
51	unassigned
71	135

a)

1st Matching table				
CAD planes	UAV planes			
11	93	138	93	85
21	113	315	113	315
31	1	52	1	70
51	3	4	116	152

b)

Final matching table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1

c)

Table 5. 5: Results removing CAD plane 71

TP	FN	FP	Completeness	Correctness
4	2	0	0.6	1

Table 5. 6: Evaluation Result

The correctness is still 100% but the number of undetected matched pairs has increased explaining the average rate of the completeness.
Despite this average completeness, the algorithm is still performing well. This may be explained by the fact that the inputs CAD-UAV planes for computing the matching result and the inputs CAD-UAV planes for computing the reference table are different, because the CAD plane 71 is not accounted for the inputs used to compute the matching result while it was maintained for the inputs of the reference table.

5.1.4 4th test Shifting point cloud by 2m in x, y, z axis.

To further evaluate the robustness of our matching algorithm, we change the inputs by shifting the point cloud by 2m. The automatically selected matched UAV-CAD planes for the first estimate matching table and final matching table are displayed respectively in Table 5.7 (b) and 5.7 (c). The performance of the matching algorithm is in Table 5.8. Table 5.7 (a) is the reference table.

Reference matching Table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1
51	unassigned
71	135

a)

1st Matching table				
CAD planes	UAV planes			
11	3	10	93	85
21	4	3	113	315
31	3	112	1	70
51	112	3	116	152
71	43	112	135	168

b)

Final matching table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1
71	135

c)

Table 5. 7: Results Shifting point cloud by 2m

TP	FN	FP	Completeness	Correctness
5	1	2	0.8	1

Table 5. 8: Evaluation Result

This result is the same as in the first case (m:n matches). Despite of the shift of 2m, the correctness is 100% and the completeness is also high. Here all the matched pairs detected by the algorithm are in the reference table. But not all the matched pairs in the reference table have been detected. That why the completeness is 80%

5.1.5 5th test: Rotation of point cloud by 5 degrees in x, y, z axis.

In this test, the same test was repeated as in 4th test. The only difference is the point cloud dataset is rotated by 5 degrees instead of being shifted.

Tables 5.9 (b, c) displays the results of the automatically selected matched UAV-CAD planes for the first estimate matching table and final matching table respectively. The performance of the matching algorithm is in Table 5.10 obtained by comparing the reference matching Table 5.9 (a) and the finale matching Table 5.9 (c)

Reference matching Table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1
51	unassigned
71	135

a)

1st Matching table				
CAD planes	UAV planes			
11	93	138	93	85
21	113	315	315	113
31	1	52	1	70
51	4	3	116	14
71	135	172	135	168

b)

Final matching table	
CAD planes	UAV Planes
11	93
21	113
21	315
31	1
71	135

c)

Table 5. 9: Results rotation point cloud by 5 degrees

TP	FN	FP	Completeness	Correctness
5	1	0	0.8	1

Table 5. 10: Evaluation Result

This result is the same as in the first case test, despite of the rotation of 5 degrees of the point cloud. We have the same conclusion as is the shift of 2 m.

5.1.6 Discussion on the accuracy of the matching

A good matching algorithm is one which combines both high completeness and high correctness (Rutzinger et al., 2009). Since for all tests performed by varying the inputs, we have an average completeness of 0.80 and average correctness of 1, we can conclude that, for this particular type of datasets, the matching algorithm is correct and reliable enough; even though for some cases the undetected matched pairs (FN) need more attention.

We notice that despite its good quality, the algorithm for some inputs, its performance in the completeness is not 100%. This means corresponding pairs which were supposed to be matched are ignored. Which are these planes which are ignored? If we analyse carefully the reference matching table, it's the CAD plane 51 which is being ignored in almost all cases. So what is "special" with this CAD plane 51? As explained before, and shown in our reference matching table (table 5.1), CAD plane 51 is unassigned. This means it is suppose to have no corresponding partner. So if our matching algorithm did not assign any corresponding UAV plane to this CAD plane; this was fully expected. So we could not have 100% for the completeness. The CAD plane 51 was also purposely put in our model with no possible corresponding partner, since our matching algorithm also ignore it, this also a proof that the matching algorithm for this datasets, is robust against bad modelling or segmentation error which may produce this extra segments or planes in one dataset without corresponding partner in the other dataset.
Despite the rotation and the shifting of the point cloud, for this particular type of datasets, the performance of the matching algorithm is also good. This confirms that the algorithm is robust against

change in distance, or change in rotation between the two datasets. However the use of distance is just reliable to some extent. Above this limit it is not. And this could be also generalised for the difference of angle parameter.
To conclude , according to Tubic et al. (2003), when using distance for matching corresponding pairs, the datasets need to be closed to each other, as the distance between the two datasets is larger, matching errors are more probable. Since our datasets were already close, our matching algorithm will be more effective if it is combined with a complete and good up-to-date CAD model when a rigid transformation is to be performed.

5.2 Accuracy of the registration

There are many methods in assessing the accuracy of a registration. The method to choose depends generally of the author of the registration. If the computation time should be considered, generally the evaluation of the rotation error, the translation error and RMS (root mean square) could be consensual parameters to investigate the accuracy of most registrations (Salvi et al., 2007).
To evaluate the registration result we look at three parameters:

- The residuals after registration
- The histograms of the residuals
- We also simulate errors by shifting and rotating the initials positions of the datasets before respectively registering them and analyzing the results.

5.2.1 The residuals after registration

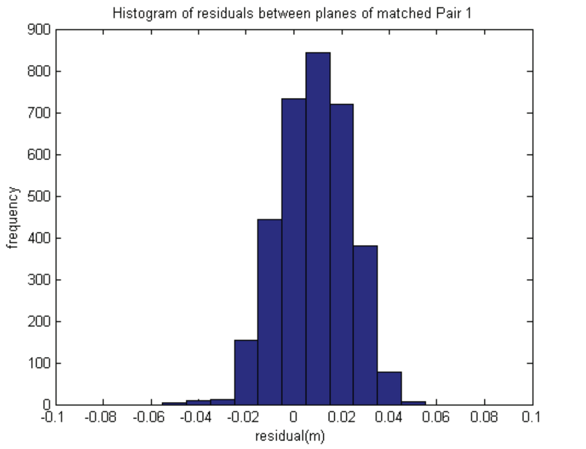
When two datasets are correctly registered, the corresponding features (planes) must be parallel (Li et al., 2013) and close to each other.
So to evaluate the result of the registration we are going to look at the geometric relationship of the corresponding plane pairs after registration by computing their mean residual and the standard deviation. Table 5.11 displays the mean residuals and respective standard deviations between points of each UAV plane and the corresponding CAD plane. By visual analysis we can notice that residuals are very small. The standard deviations are low less than 3 cm which make the registration globally correct.

Corresp. Pairs ID	11 - 93	21 - 113	21 - 315	31 - 1	71 - 135
Mean (m)	0.014	0.037	0.033	0.036	0.068
Standard deviation (m)	0.010	0.014	0.023	0.019	0.026

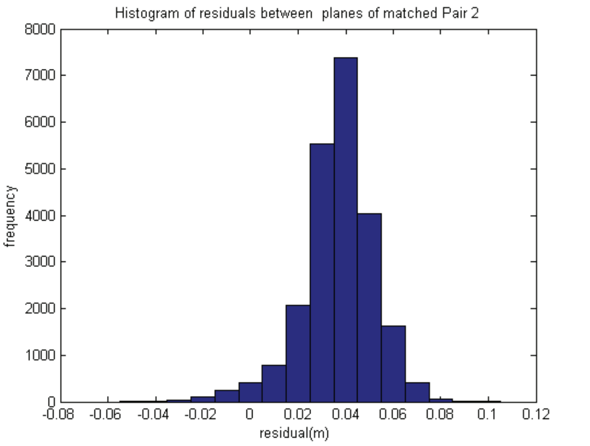
Table 5. 11: Mean residual (mean distance) and mean standard deviation between points of each UAV plane and the corresponding CAD plane and their standard deviation.

5.2.2 The histograms of the residuals

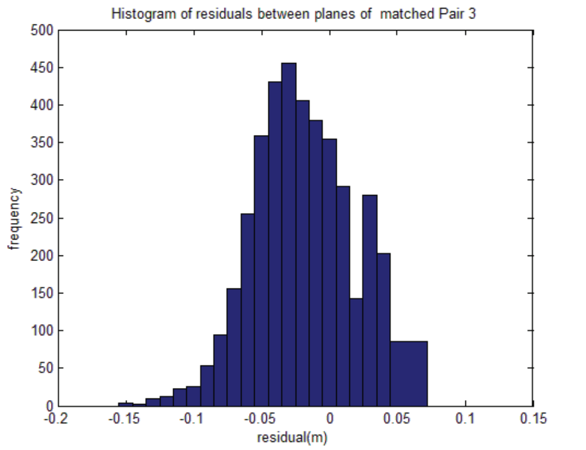
To further analyse this result we can look at the histograms of these residuals. The histograms are displayed in Figure 5.1.



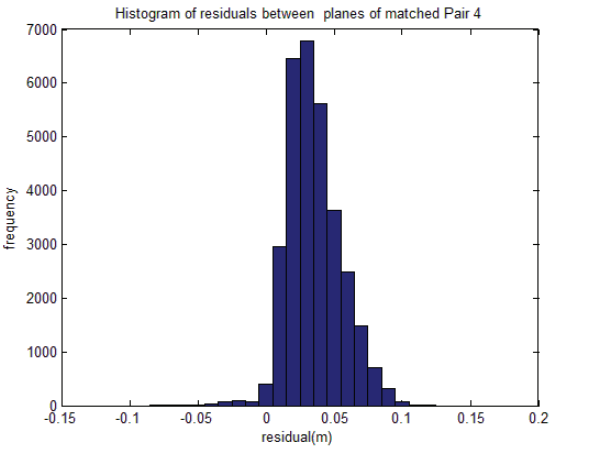
a)Histogram of residuals of matched plane pair CAD 11 and UAV 93



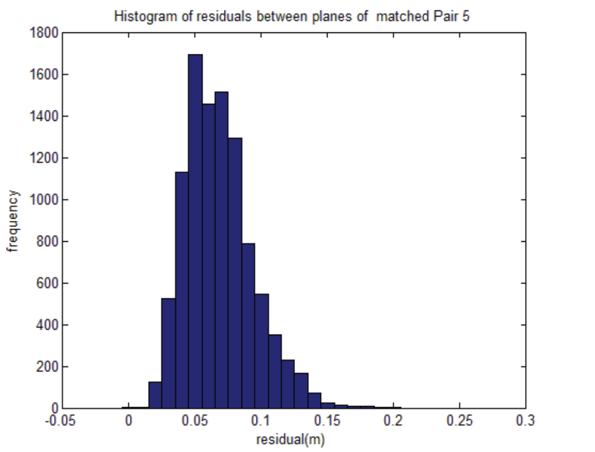
b)Histogram of residuals of matched plane pair CAD 21 and UAV 113



c)Histogram of residuals of matched plane pair CAD 21 and UAV 315



d)Histogram of residuals of matched plane pair CAD 31 and UAV 1



d)Histogram of residuals of matched plane pair CAD 71 and UAV 135

Figure 5.1: Histograms of residuals between registered corresponding planes pairs.

In general when it is correct, the histograms of the residual of a registration should follow a normal distribution (Chen & Medioni, 1992; Thapa, 2009; Tubic et al., 2003). About the histograms in Figure 5.1, the first one has a normal distribution but for the others the tails are slightly right or left skewed. This will be elaborated in the discussion section.

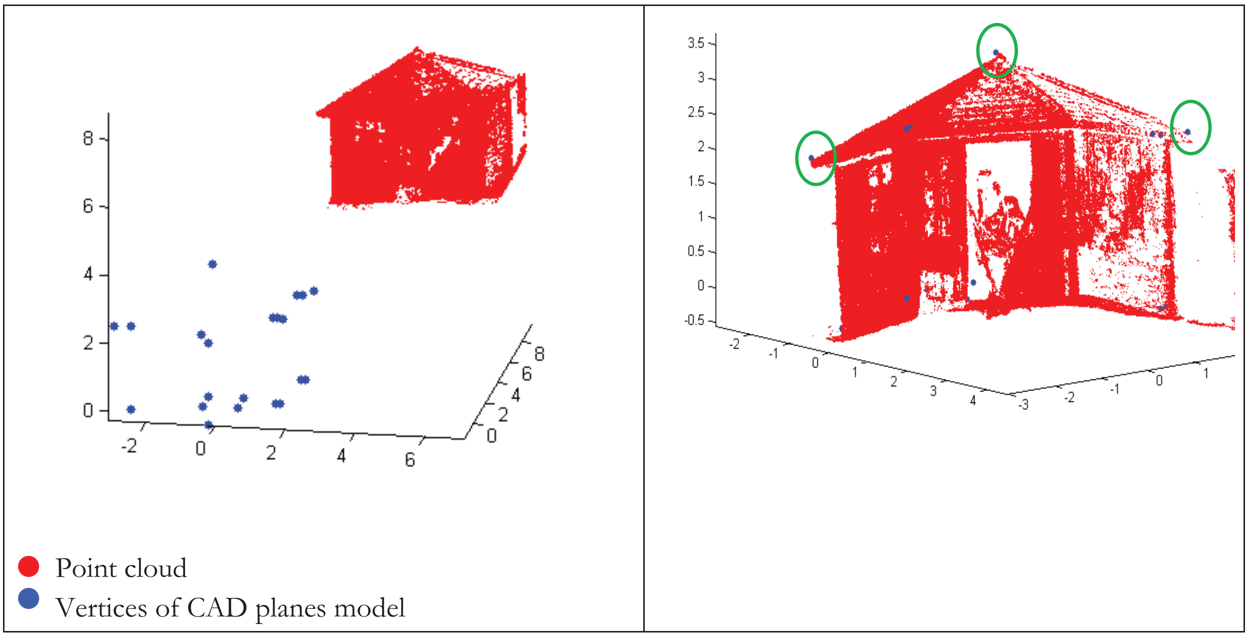
5.2.3 Shifting and rotating the initials positions of the datasets

After the computation of the transformation and the registration of the two datasets as they are in their initial positions, to further evaluate the registration we are going to respectively change the initial positions of our two datasets by a known offset and known rotation angle respectively. Then, we are going to analyse how the registration will behave with respect to these changes.

5.3.2.1 Shifting point cloud by 5m in x, y, z axis

The point cloud is shifted by 5m. Table 5.12 displays the result of the automatically selected CAD-UAV planes of the first estimate matching table. The final matching table obtained as a result of the matching algorithm is shown in Table 5.13. These matched pairs were used to:

- Compute the transformation parameters (Table 5.14)
- Compute the mean residual and mean standard deviation of each matched pair used during the computation of transformation parameters. (Table 5.15 and 5.16 respectively).
- Figure 5.2 shows an example of the datasets before and after registration. Some of the offsets between the two datasets after registration are circled and will be described in the discussion



a) b)

Figure 5.2: Point cloud shifted by 5m and vertices of CAD planes model before registration (a) and after registration (b)

CAD Planes	UAV Planes			
11	112	3	93	85
21	112	3	113	315
31	112	3	1	70
51	112	3	116	152
71	112	3	135	168

Table 5. 12: Matching Table

CAD planes	UAV Planes
11	93
21	113
21	315
31	1
71	135

Table 5. 13: Final Matching table

Omega (degree)	Phi (degree)	Kappa (degree)	Tx (m)	Ty(m)	Tz(m)
-0.080	0.395	-1.264	4.528	5.331	5.209

Table 5. 14: Result of six transformation parameters: 3 rotation angles, 3 translations.

Corresponding pair IDs	11-93	21-113	21-315	31-1	71-135
Mean residual (distance from points to corresponding plane). (m)	0.061	0.068	0.030	0.025	0.274

Table 5. 15: Mean residual (mean distance) between points of each UAV plane and the corresponding CAD plane for each corresponding CAD-UAV plane pair.

Corresponding pair IDs	11-93	21-113	21-315	31-1	71-135
Mean standard deviation (m)	0.015	0.015	0.022	0.015	0.026

Table 5. 16: Mean standard deviation between points of each UAV plane and the corresponding CAD plane for each corresponding CAD-UAV plane pair.

Comparison between the registration of the initial position and the registration after the 5m shift

The result in Table 5.17 was derived by comparing the result of the computation of the transformation parameters of the datasets in their initial position (Chapter 4, Table 4.4) and the result of the computation of the transformation parameter of the dataset after a shift of 5m in x, y, z axis (Table 5.14).

$\Delta\gamma(degree)$	$\Delta\varphi(degree)$	$\Delta\kappa(degree)$	ΔTx (m)	ΔTy (m)	ΔTz (m)
0	0	0	4.648	5.131	5.097

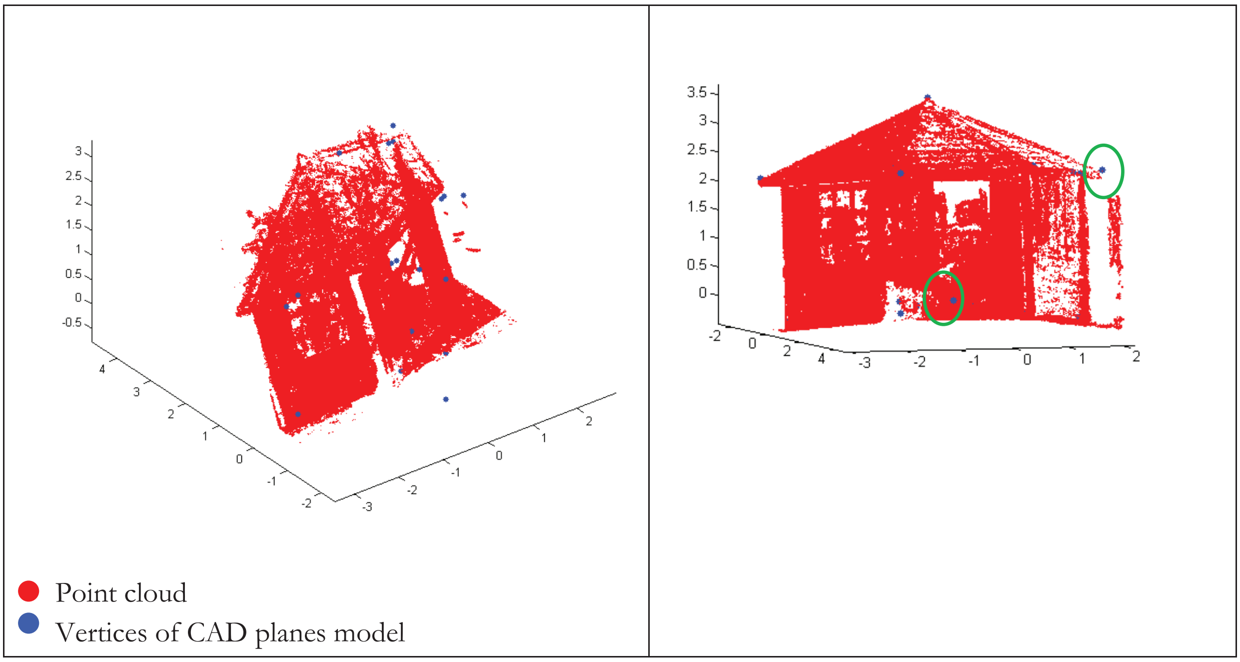
Table 5. 17: Result of comparison between the registration of the initial position and the registration after the 5m shift

As expected the translation has increased and the rotation has not changed. Since the data was only shifted by 5 m and not rotated, this result was fully expected. However if we look carefully to the increase in the translation it is 4.648m , 5.131m, 5.097m for Tx. Ty, Tz respectively. And for all these directions the increase should have been exactly 5m as the shift was 5m. Since the matching tables of the datasets in their initial state and after the shifting are same, how to explain these small differences? The negligible increases and decreases in the 5 m may be explained by the nature of the UAV planes which may be noisy. Furthermore, it also related, as explained before to the nature of CAD model planes which are slightly tilted due to errors in the manual modelling.

5.3.2.2 Rotate point cloud by 10 degrees in: x, y, z axis

The point cloud is now rotated by 10 degrees. As in the case of the shift, Table 5.18 displays the result of the automatically selected CAD-UAV planes of the first estimate matching. The final matching table obtained as a result of the matching algorithm is shown in Table 5.19. These matched pairs were used to:

- Compute the transformation parameters (Table 5.20)
- Compute the mean residual and mean standard deviation or each matched pair used during the computation of transformation parameters. (Table 5.21 and 5.22 respectively)
- Figure 5.3 shows an example of the datasets before and after registration. Some of the offsets between the two datasets after registration are circled and will be described in the discussion.



a) b)

Figure 5.3: Point cloud rotated by 10 degrees and vertices of CAD planes model before registration (a) and after registration (b)

CAD Planes	UAV planes			
11	93	138	85	93
21	315	315	315	113
31	1	52	315	113
51	240	43	116	3
71	135	172	135	172

Table 5. 18: Matching Table

CAD planes	UAV Planes
11	93
21	113
21	315
31	1
71	135

Table 5. 19: Final Matching Table

Omega (degree)	Phi (degree)	Kappa (degree)	Tx (m)	Ty(m)	Tz(m)
-11.691	-7.544	-12.956	-0.120	0.200	0.112

Table 5. 20: Result of six transformation parameters: 3 rotation angles, 3 translations

Corresponding pair IDs	11-93	21-113	21-315	31-1	71-135
Mean residual (distance from points to corresponding plane). (m)	0.014	0.037	0.033	0.036	0.068

Table 5. 21: Mean residual (mean distance) between points of each UAV plane and the corresponding CAD plane for each corresponding CAD-UAV plane pair.

Corresponding pair IDs	11-93	21-113	21-315	31-1	71-135
Mean standard deviation (m)	0.010	0.014	0.023	0.019	0.026

Table 5. 22: Mean standard deviation between points of each UAV plane and the corresponding CAD plane for each corresponding CAD-UAV plane pair.

Comparison between the registration of the initial position and the registration after 10 degrees rotation

The result in Table 5.23 was derived by comparing the result of the computation of the transformation parameters of the datasets in their initial position (Chapter 4, Table 4.4) and the result of the computation of the transformation parameter of the dataset after a rotation of 10 degrees in x, y, z axis (Table 4.20).

$\Delta\gamma(degree)$	$\Delta\varphi(degree)$	$\Delta\kappa(degree)$	ΔTx	ΔTy	ΔTz
-11.611	-7.939	-11.692	0	0	0

Table 5. 23: Comparison between the registration of the initial position and the registration after 10 degrees rotation

For the rotation of the data by 10 degrees, we can have the same reasoning has in the case of the shifting by 5m described above.
As expected the rotation has increased and the translation has not change. Since the data was only rotated by 10 degrees. This result was fully also expected. The increases and decreases in the 10 degrees rotations (-11.611, -7.939, -11.692) may be explained by the nature of the UAV planes which may be noisy. Furthermore, it also related, as explained before to the nature of CAD model planes which are slightly tilted due errors in the manual modelling. Also when the rotation angle between the two datasets increases the registration is less precise explaining this noticeable difference or around 2 degrees (10 - 7.939) for Phi.

5.3.3 Discussion on the accuracy of the registration

If we analyse these results we can conclude that the registration is correct. These results have been demonstrated by the nature of the residuals and the histograms. The registration is also very robust to changes of the positions of the initial datasets to some extent.
However after registration the corresponding planes should be parallel. Even though the residuals are very low, still it shows some offsets (figures 5.2 and 5.3). This indicates some errors. According to (Bergevin et al., 1996) the accuracy of registration may be influenced by two types of errors: acquisition errors or/ and registration errors. For the type of datasets we used, we could add a third error: the errors within the CAD model due to manual modelling errors. As stated before, the result of registration is closely link to the nature of the matched features. If we analyse the histograms, we notice that although they should follow generally a normal distribution, the tails are slightly right or left skewed. This skew indicates some problems within the planarity of the segments registered. We know that CAD model have good planar segments, however for the specific datasets we used they are slightly tilted due to modelling errors. The datasets registered involved CAD model and Point cloud, the planarity problems must be also within the point cloud segments. This may be explained by the fact we have imaged based point cloud which is generally noisy. And this noise may come as outliers and affect the planarity of the segments. Occlusions present within the sets of images used to generate the point cloud may also produce noise which will affect the planarity of the point cloud segments. And naturally when tilted planes (from CAD model) and segments with planarity problems (from point cloud) are registered together, the planes after registration will not be completely close and parallel, we may have some offsets. This explains the amount of residuals (errors) we have after registration. Errors which are a combination of both systematic error (acquisition errors) and registration errors (noisy UAV segments) but also errors from the CAD model.
Another source of registration error is the use of false matched features during the registration process. However, this is not our case because only good matched pairs were used. The matching algorithm was robust enough to discard false matched pairs.
We can conclude that the systematic errors and the registration errors are interdependent in our case. Because registration errors may result from matched features with planarity problems and the nature of the features may partly also depend here on the acquisition of the data (systematic errors).

6. CONCLUSION AND RECOMMADATIONS

6.1. Conclusion

With the unmanned Aerial vehicle (UAV) it is possible to acquire high resolution images at a low cost. However, the main limitation is with GNSS/INS systems used on board UAVs. It has a low cost but it is not accurate. If we recall our assumption, UAV images can be oriented with quite a high accuracy but location with respect to coordinate frame is uncertain because of limited onboard GPS positioning capabilities. This will result in poor initial orientation with offset of around 3.5 m and angle of 5 to 10 degrees.

To better orient the images we may think of having high quality navigation device (IMU or RTK techniques) as an alternative to the inaccurate GPS to improve the accuracy. As we elaborated in this study this will be expensive and the UAV will lose its main advantage i.e its affordability.

The other alternative is to orient the images. The aim of this study was the automatic registration of architectural (CAD) models of buildings to airborne images.

The registration of the CAD model and the point cloud was performed using the assumption the two datasets are close (offset 3 to 4m). This study has proven that it can be done with a high accuracy. However our study has shown that the following challenges have to be identified and solved before performing the registration.

- A good, reliable and up-to-date CAD model, because this study has revealed that a bad or not up-to-date CAD model can have negative effects on the overall registration process and results.
- Reliable point cloud segments. Outcome of a feature based registration is closely linked to the nature of features used during the registration. As highlighted in this study, having reliable planar point cloud segments is important. So the type of segmentation and strategy used is also critical. Image based point cloud is noisy and the strategy of segmentation applied should be able to extract a maximum planes with negligible amount of noise.
- A very good matching strategy. This study has shown that false corresponding pairs but also undetected matched pairs are source of errors for the registration. So to have a good matching strategy is critical. The look for corresponding pairs should be combined to the ability to discard wrong matched features.

The registration of imaged base point cloud and CAD model is very promising. In fact the registration of point cloud and CAD model is the main step in many applications of computer vision like damage assessment, construction progress monitoring, automatic inspection. So the success and accuracy of the registration are critical.

6.2. Answers to the research questions

1. What are the available techniques for 3D/3D registration?

From our study we pointed out the following techniques

- Point to point registration where the transformation parameters are evaluated using corresponding 3D points from both datasets.

- Plane to plane registration where a minimum of 3 non parallel corresponding planes are extracted from both datasets to perform the registration
- And finally a combination of different features like point to plane to perform the registration

2. Which of these are more suitable to both 3D CAD model and the 3D point cloud?

In this research, methods which used features like point to plane or plane to plane have proven to be more reliable and successful in the registration due to the nature of the datasets.

3. In case of feature based registration, which features are more robust to occlusion problems?

This research has demonstrated that point and lines are very sensitive to noise and clutters. In the other hand, planes are more robust to noise. Furthermore planes are more distinguishable and less difficult to extract than point. Therefore in case of feature based registration with occlusion, registration using planes are more appropriate.

4. Which search strategy is more suitable for looking for corresponding features to match?

Taking into account the two datasets are close, compatibility of normals and distance properties were used to find correspondences between the two datasets. A one to many correspondences were used before refining it to remove false correspondences to make sure the right corresponding partner were selected.

5. How accurate and successful is the registration algorithm especially with occlusions/gaps?

The completeness and correctness of the matching algorithm was based on correctly matched planes and false matched planes. The average completeness and correctness are 80% and 100% respectively, we can conclude that, for this particular type of datasets, the accuracy of the matching algorithm is high and reliable enough. The completeness is less than 100%. This was expected as we had an assigned CAD plane (CAD plane with no partner). This also is a proof that the algorithm is robust against bad modelling or segmentation errors and also occlusions/gaps.

6.3. Recommendations

To improve the algorithms, followings are some recommendations:

- In this research we have used only big-sized UAV planes after segmentation. Non planar segments could affect the result of the registration. To increase the accuracy of the registration, further research could focus on developing a method to remove automatically non planar UAV segments after the segmentation before performing the matching and registration.

- In this research in our matching algorithm, we selected good combinations by systematically testing all combinations. This may be computationally expensive when we have a big number of planar features. To reduce the time of computation, future work can focus on big-sized planes, after extracting all planes in both datasets. Furthermore, to reduce the search space, among this big-sized planes we can select only the ones which are spread as much as possible in space because this will give in better result.

- Feature based registration result is closely linked to the nature of extracted feature. For manmade structure like building planar feature are expected. For non structured surface, our method need further improvement in order to be applied due to difficulty of extracting reliable features for matching when we have non structured surfaces.
- Further study could use additional geometric properties to check the effective overlap of planar faces after the matching during registration of 3D CAD model and the 3D point cloud.

LIST OF REFERENCES

Alobeid, A., Jacobsen, K., & Heipke, C. (2010). Comparison of Matching Algorithms for DSM Generation in Urban Areas from Ikonos Imagery. *Photogrammetric Engineering and Remote Sensing, 76*(9), 1041-1050.

Armenakis, C., Gao, Y., & Sohn, G. (2013). Co-registration of aerial photogrammetric and LiDAR point clouds in urban environments using automatic plane correspondence. *Applied Geomatics, 5*(2), 155-166. doi: 10.1007/s12518-013-0105-9

Bergevin, R., Soucy, M., Gagnon, H., & Laurendeau, D. (1996). Towards a general multi-view registration technique. *Pattern Analysis and Machine Intelligence, IEEE Transactions on, 18*(5), 540-547. doi: 10.1109/34.494643

Besl, P. J., & McKay, N. D. (1992). A METHOD FOR REGISTRATION OF 3-D SHAPES. *Ieee Transactions on Pattern Analysis and Machine Intelligence, 14*(2), 239-256. doi: 10.1109/34.121791

Böhm, J., Brenner, C., Gühring, J., & Fritsch, D. (2000). *Automated extraction of features from cad models for 3d object recognition.* Paper presented at the in ISPRS Congress 2000.

Bosche, F. (2010). Automated recognition of 3D CAD model objects in laser scans and calculation of as-built dimensions for dimensional compliance control in construction. *Advanced Engineering Informatics, 24*(1), 107-118. doi: 10.1016/j.aei.2009.08.006

Bosche, F. (2012). Plane-based registration of construction laser scans with 3D/4D building models. *Advanced Engineering Informatics, 26*(1), 90-102. doi: 10.1016/j.aei.2011.08.009

Bosché, F. N. (2008). *Automated recognition of 3d cad model objects in dense laser range point clouds.* University of Waterloo.

Boudet, L. (2007). *Auto-qualification de données géographiques 3D par appariement multiimage et classification supervisée. Application au bâti en milieu urbain dense.* PhD thesis, Université Paris-Est, Marne-la-Vallée.

Boukebbab, S., Bouchenitfa, H., Boughouas, H., & Linares, J. M. (2007). Applied iterative closest point algorithm to automated inspection of gear box tooth. *Computers & Industrial Engineering, 52*(1), 162-173. doi: http://dx.doi.org/10.1016/j.cie.2006.12.001

Boulanger, P., DHOME, M., JUTARD, A., PYZAK, D., REDARCE, H., & TICHKIEWITCH, S. (1996). MISE EN CORRESPONDANCE DE DONNEES 3D AVEC UN MODELE CAO: APPLICATION A L'INSPECTION AUTOMATIQUE.

Brandou, V., Allais, A. G., Perrier, M., Malis, E., Rives, P., Sarrazin, J., & Sarradin, P. M. (2007, 18-21 June 2007). *3D Reconstruction of Natural Underwater Scenes Using the Stereovision System IRIS.* Paper presented at the OCEANS 2007 - Europe.

Brenner, C., & Dold, C. (2007). Automatic relative orientation of terrestrial laser scans using planar structures and angle constraints. *Proc. Laser Scanning*, 84-89.

Brenner, C., Dold, C., & Ripperda, N. (2008). Coarse orientation of terrestrial laser scans in urban environments. *ISPRS Journal of Photogrammetry and Remote Sensing, 63*(1), 4-18. doi: 10.1016/j.isprsjprs.2007.05.002

Cabrelles, M., Seguí, A., Navarro, S., Galcerá, S., Portalés, C., & Lerma, J. (2010). 3D Photorealistic Modelling of Stone Monuments by Dense Image Matching. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 38*(5), 121-124.

Chen, Y., & Medioni, G. (1992). Object modelling by registration of multiple range images. *Image and Vision Computing, 10*(3), 145-155. doi: http://dx.doi.org/10.1016/0262-8856(92)90066-C

Chiabrando, F., Nex, F., Piatti, D., & Rinaudo, F. (2011). UAV and RPV systems for photogrammetric surveys in archaelogical areas: two tests in the Piedmont region (Italy). *Journal of Archaeological Science, 38*(3), 697-710.

Chiroiu, L., Adams, B., & Saito, K. (2006). Advanced Techniques in Modelling, Response and Recovery. In C. Oliveira, A. Roca & X. Goula (Eds.), *Assessing and Managing Earthquake Risk* (Vol. 2, pp. 427-448): Springer Netherlands.

David, P., DeMenthon, D., Duraiswami, R., & Samet, H. (2003, 18-20 June 2003). *Simultaneous pose and correspondence determination using line features.* Paper presented at the Computer Vision and Pattern Recognition, 2003. Proceedings. 2003 IEEE Computer Society Conference on.

Doucette, P., Theiss, H., Marshall, J., Dolloff, J., Lenihan, M., Mikhail, E. M., & Johanesen, T. E. (2013). Measurement and Automation Practices in Photogrammetry. In J. C. McGlone (Ed.), *Manual of photogrammetry* (pp. 981-982).

Dubuisson, M. P., & Jain, A. K. (1994, 9-13 Oct 1994). *A modified Hausdorff distance for object matching.* Paper presented at the Pattern Recognition, 1994. Vol. 1 - Conference A: Computer Vision & Image Processing., Proceedings of the 12th IAPR International Conference on.

Eguchi, R., Huyck, C., Ghosh, S., Adams, B., & McMillan, A. (2010). Utilizing New Technologies in Managing Hazards and Disasters. In P. S. Showalter & Y. Lu (Eds.), *Geospatial Techniques in Urban Hazard and Disaster Analysis* (Vol. 2, pp. 295-323): Springer Netherlands.

El-Hakim, S., Whiting, E., Gonzo, L., & Girardi, S. (2005). 3D Reconstruction of Complex Architectures from Multiple Data.

Gerke, M. (2009). Dense matching in high resolution oblique airborne images. *CMRT09*, 77-82.

Golparvar-Fard, M., Bohn, J., Teizer, J., Savarese, S., & Pena-Mora, F. (2011). Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques. *Automation in Construction, 20*(8), 1143-1155. doi: DOI 10.1016/j.autcon.2011.04.016

Golparvar-Fard, M., Peña-Mora, F., & Savarese, S. (2009). Application of D4AR–A 4-Dimensional augmented reality model for automating construction progress monitoring data collection, processing and communication.

Grant, D., Bethel, J., & Crawford, M. (2012). Point-to-plane registration of terrestrial laser scans. *ISPRS Journal of Photogrammetry and Remote Sensing, 72*(0), 16-26. doi: http://dx.doi.org/10.1016/j.isprsjprs.2012.05.007

Gressin, A., Mallet, C., Demantké, J., & David, N. (2013). Towards 3D lidar point cloud registration improvement using optimal neighborhood knowledge. *ISPRS Journal of Photogrammetry and Remote Sensing, 79*(0), 240-251. doi: http://dx.doi.org/10.1016/j.isprsjprs.2013.02.019

Gruen, A., Remondino, F., & Zhang, L. (2005). The Bamiyan project: multi-resolution image-based modeling. *ISPRS Highlights, 10*(2).

Hassan, F. M., MatJafri, M. Z., & Lim, H. S. (2011, 25-28 Sept. 2011). *Contextual classification of Cropcam UAV high resolution images using frequency-based approach for land use/land cover mapping case study: Penang Island.* Paper presented at the Industrial Electronics and Applications (ISIEA), 2011 IEEE Symposium on.

Hirschmuller, H. (2005, 20-25 June 2005). *Accurate and efficient stereo processing by semi-global matching and mutual information.* Paper presented at the Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on.

Ip, C. Y., & Gupta, S. K. (2007). Retrieving matching CAD models by using partial 3D point clouds. *Computer-Aided Design & Applications, 4*(5), 629-638.

Jaw, J., & Chuang, T. (2008). Feature-based registration of terrestrial lidar point clouds. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37*, 303-308.

Khoshelham, K. (2010, 15-17 Sept. 2010). *Automated localization of a laser scanner in indoor environments using planar objects.* Paper presented at the Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on.

Khoshelham, K., Nardinocchi, C., Frontoni, E., Mancini, A., & Zingaretti, P. (2010). Performance evaluation of automated approaches to building detection in multi-source aerial data. *ISPRS Journal of Photogrammetry and Remote Sensing, 65*(1), 123-133. doi: http://dx.doi.org/10.1016/j.isprsjprs.2009.09.005

Kim, C., Lee, J., Minwoo, C., & Kim, C. (2010). Fully automated registration of 3D CAD model with point cloud from construction site.

Kim, C., Son, H., & Kim, C. (2013). Automated construction progress measurement using a 4D building information model and 3D data. *Automation in Construction, 31*(0), 75-82. doi: http://dx.doi.org/10.1016/j.autcon.2012.11.041

Kim, J., Lee, S., Ahn, H., Seo, D., Park, S., & Choi, C. (2013). Feasibility of employing a smartphone as the payload in a photogrammetric UAV system. *ISPRS Journal of Photogrammetry and Remote Sensing, 79*(0), 1-18. doi: http://dx.doi.org/10.1016/j.isprsjprs.2013.02.001

Koutsoudis, A., Vidmar, B., Ioannakis, G., Arnaoutoglou, F., Pavlidis, G., & Chamzas, C. (2013). Multi-image 3D reconstruction data evaluation. *Journal of Cultural Heritage*(0). doi: http://dx.doi.org/10.1016/j.culher.2012.12.003

Lam, J., Kusevic, K., Mrstik, R., Harrap, P., & Greenspan, M. (2010). *Urban scene extraction from mobile ground based lidar data.* Paper presented at the Proceedings of 3DPVT.

Lelong, C., Burger, P., Jubelin, G., Roux, B., Labbé, S., & Baret, F. (2008). Assessment of Unmanned Aerial Vehicles Imagery for Quantitative Monitoring of Wheat Crop in Small Plots. *Sensors, 8*(5), 3557-3585.

Li , M., Cheng, L., Gong, J., Liu, Y., Chen, Z., Li, F., . . . Song, X. (2008). Post-earthquake assessment of building damage degree using LiDAR data and imagery. *Science in China Series E-Technological Sciences, 51*, 133-143. doi: 10.1007/s11431-008-6014-1

Li, X., Li, W., Jiang, H., & Zhao, H. (2013). Automatic evaluation of machining allowance of precision castings based on plane features from 3D point cloud. *Computers in Industry*(0). doi: http://dx.doi.org/10.1016/j.compind.2013.06.003

Mani, G.-F., Feniosky, P.-M., & Silvio, S. (2009). DAR- A 4-dimensional augmented reality model for automating construction progress monitoring data collection, processing and communication4. *Journal of Information Technology in Construction, Special Issue in Next Generation Construction IT*, 129-153.

Marshall, A. D., Martin, R. R., & Hutber, D. (1991). Automatic inspection of mechanical parts using geometric models and laser range finder data. *Image and Vision Computing, 9*(6), 385-405. doi: http://dx.doi.org/10.1016/0262-8856(91)90005-A

Monnier, F., Vallet, B., Paparoditis, N., Papelard, J. P., & David, N. (2013). REGISTRATION OF TERRESTRIAL MOBILE LASER DATA ON 2D OR 3D GEOGRAPHIC DATABASE BY USE OF A NON-RIGID ICP APPROACH.

Musialski, P., Wonka, P., Aliaga, D. G., Wimmer, M., Gool, L., & Purgathofer, W. (2013). *A survey of urban reconstruction.* Paper presented at the Computer Graphics Forum.

Prieto, F., Redarce, H., Lepage, R., & Boulanger, P. (1999). A non contact CAD based inspection system. *Quality Control by Artificial Vision*, 133-138.

Pu, S., & Vosselman, G. (2006). Automatic extraction of building features from terrestrial laser scanning. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36*(5), 25-27.

Rabbani, T., & van den Heuvel, F. (2005). *Automatic point cloud registration using constrained search for corresponding objects.* Paper presented at the Proceedings of 7th Conference on Optical.

Rabbani, T., van Den Heuvel, F., & Vosselmann, G. (2006). Segmentation of point clouds using smoothness constraint. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36*(5), 248-253.

Ramalingam, S., & Taguchi, Y. (2013). A Theory of Minimal 3D Point to 3D Plane Registration and Its Generalization. *International Journal of Computer Vision, 102*(1-3), 73-90. doi: 10.1007/s11263-012-0576-x

Ramalingam, S., Taguchi, Y., Marks, T., & Tuzel, O. (2010). P2Π: A Minimal Solution for Registration of 3D Points to 3D Planes. In K. Daniilidis, P. Maragos & N. Paragios (Eds.), *Computer Vision – ECCV 2010* (Vol. 6315, pp. 436-449): Springer Berlin Heidelberg.

Remondino, F., Barazzetti, L., Nex, F., Scaioni, M., & Sarazzi, D. (2011). *UAV Photogrammetry for Mapping and 3D Modeling - Current Status and Future Perspectives*. Paper presented at the International Conference on Unmanned Aerial Vehicle in Geomatics (UAV-g), Zurich, Switzerland.

Remondino, F., & El-Hakim, S. (2006). Image-based 3D Modelling: A Review. *The Photogrammetric Record, 21*(115), 269-291.

Rottensteiner, F. (2002). *Semi - automatic extraction of buildings based on hybrid adjustment using 3D surface models and management of building data in a TIS topographical information system*. Wien: Technische Universität Wien.

Rutzinger, M., Rottensteiner, F., & Pfeifer, N. (2009). A Comparison of Evaluation Techniques for Building Extraction From Airborne Laser Scanning. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of, 2*(1), 11-20. doi: 10.1109/JSTARS.2009.2012488

Salvi, J., Matabosch, C., Fofi, D., & Forest, J. (2007). A review of recent range image registration methods with accuracy evaluation. *Image and Vision Computing, 25*(5), 578-596. doi: http://dx.doi.org/10.1016/j.imavis.2006.05.012

Sande, C. v. d., Soudarissanane, S., & Khoshelham, K. (2010). Assessment of Relative Accuracy of AHN-2 Laser Scanning Data Using Planar Features. *Sensors, 10*(9), 8198-8214.

Schenk, T., Krupnik, A., & Postolov, Y. (2000). Comparative study of surface matching algorithms. *International Archives of Photogrammetry and Remote Sensing, 33*(B4), 518-524.

Schweier, C., Markus, M., & Steinle, E. (2004). Simulation of earthquake caused building damages for the development of fast reconnaissance techniques. *Natural Hazards and Earth System Science, 4*(2), 285-293.
Stamos, I., Liu, L., Chen, C., Wolberg, G., Yu, G., & Zokai, S. (2008). Integrating automated range registration with multiview geometry for the photorealistic modeling of large-scale scenes. *International Journal of Computer Vision, 78*(2-3), 237-260. doi: 10.1007/s11263-007-0089-1
Thapa, A. (2009). Semantic feature based registration of laser point clouds: Cité.
Tubic, D., Hébert, P., & Laurendeau, D. (2003). A volumetric approach for interactive 3D modeling. *Computer Vision and Image Understanding, 92*(1), 56-77. doi: http://dx.doi.org/10.1016/j.cviu.2003.07.001
Vosselman, G. (2009). *Advanced point cloud processing.* Paper presented at the Photogrammetric week.
Vosselman, G., Gorte, B. G., Sithole, G., & Rabbani, T. (2004). Recognising structure in laser scanner point clouds. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 46*(8), 33-38.
Wang, H. (2013). An Improved Method Based on Quaternion and Planar Segmentation Fit in 3D Registration. In Z. Zhong (Ed.), *Proceedings of the International Conference on Information Engineering and Applications (IEA) 2012* (Vol. 218, pp. 717-723): Springer London.
Wang, T., Yan, L., & Mooney, P. (2011, June 29 2011-July 1 2011). *Dense point cloud extraction from UAV captured images in forest area.* Paper presented at the Spatial Data Mining and Geographical Knowledge Services (ICSDM), 2011 IEEE International Conference on.
Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., & Reynolds, J. M. (2012). 'Structure-from-Motion' photogrammetry: A low-cost, effective tool for geoscience applications. *Geomorphology, 179*, 300-314. doi: 10.1016/j.geomorph.2012.08.021
Xie, Z., Xu, S., & Li, X. (2010). A high-accuracy method for fine registration of overlapping point clouds. *Image and Vision Computing, 28*(4), 563-570. doi: http://dx.doi.org/10.1016/j.imavis.2009.09.006
Zhang, Z. (1993). Le Probleme de la mise en correspondance: l'etat de l'art.
Zhang, Z. (1994). ITERATIVE POINT MATCHING FOR REGISTRATION OF FREE-FORM CURVES AND SURFACES. *International Journal of Computer Vision, 13*(2), 119-152. doi: 10.1007/bf01427149
Zitova, B., & Flusser, J. (2003). Image registration methods: a survey. *Image and Vision Computing, 21*(11), 977-1000. doi: 10.1016/s0262-8856(03)00137-9