FEATURE BASED MATCHING BETWEEN UAV BASED POINT CLOUD & ALS DATA

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March, 2014

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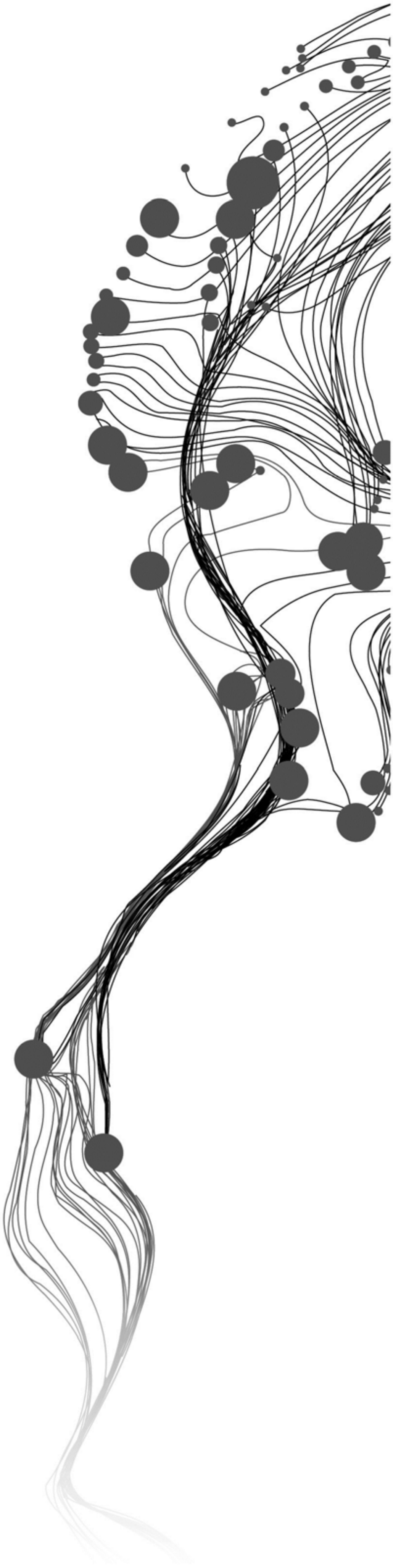

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NAYYER SALEEM
Enschede, The Netherlands, March, 2014

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.
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ABSTRACT

Collection of geospatial data through UAV photogrammetric systems is emerging as useful technique for several photogrammetric applications e.g. image acquisition, rectified images, point clouds, DSM generation, 3D modelling, etc. Cost effectiveness of UAV photogrammetric systems is main reason for their rapid development and usage for various purposes by different communities. UAV's image-based point cloud of a topographic area is exploited for feature-based registration with airborne Lidar data of same area.

UAV's image-based point cloud data become an effective alternate to point cloud data obtained by airborne Lidar systems. However certain factors affect positional accuracy of UAV's data. Prominent factors are lack of IMU on UAV systems and usage of imprecise GPS due to its payload capacity. These two reasons cause for an unknown shift in UAV data, therefore direct or indirect sensor orientation is performed for its correction. Beside both these methods, modern algorithms exploit several geometric features like point, lines, polygon, sphere, torus, etc. for an automated feature based registration with ALS dataset. This conducted research is also about feature-based registration between 3D point clouds obtained by two different sources for same area. RANSAC algorithm is exploited for plane extraction from both datasets. Distance and angle difference are used as initial measures to extract correspondences from both datasets. This study proves that 1: many approach is much more realistic and reliable than 1:1 approach in an urban scene. Mean and standard deviation of distance between ALS plane and UAV corresponding points are used as measures to analyse these initial correspondences.

Developed algorithm reliably detects features from both datasets, extracts reliable correspondences from UAV dataset, assesses them for their validation and finally registered both datasets by obtaining transformation parameters. Plane-to-plane and point-to-plane approaches are executed for registration purposes. According to results obtained, an automated feature-based registration can be considered as trustworthy option for 3D point cloud data registration. However, quality of datasets, pre-processing quality and corresponding features correctness can affect registration accuracy.

Keywords: UAV, ALS, Feature-based matching, 3D Registration

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LIST OF ABBREVIATIONS

3D	Three Dimensional
ALS	Airborne Laser Scanning
DSM	Digital Surface Modelling
GPS	Global Positioning System
ICP	Iterative Closest Point
IMU	Inertial Measurement Unit
RANSAC	RANdom SAmple Consensus
SFM	Structure from Motion
SGM	Semi global matching
UAV	Unmanned Aerial Vehicle

1. INTRODUCTION

1.1. Motivation and Problem Statement

Unmanned aerial vehicle (UAV) based photogrammetry has emerged as a convenient and cost-effective practice in community of remote sensing with different applications. UAV development has been driven primarily by military users and then by civilian users for earth observation and scientific data collection purposes (Watts et al., 2012). Initially, high resolution images were sole product of UAV but with the advent of technologies in computer vision, several photogrammetric products like point cloud, DSM, orthoimages, etc. have also been obtained through these images using specific software. Point cloud is mainly product of airborne laser scanning (ALS) but can also be obtained from UAV images using dense image matching approach. Both datasets are different in density and accuracy.

Airborne laser scanning (ALS) is well matured and sophisticated technique which delivers 3D point data with high positional accuracy (Vosselman & Mass, 2010). However, positional accuracy of 3D points acquired by using UAV images is often less accurate and have varying point density as compared to ALS points (Golparvar-Fard et al., 2011). UAV point cloud is obtained after UAV's image orientation through structure from motion (SFM) and dense image matching technique. Due to payload limitations for UAV photogrammetric systems, high precise GPS and IMU cannot be mounted on them for direct georeferencing. 3D similarity transformation issue arises between both datasets due to this drawback, which involves translation, rotation and scale. However use of micro GPS on UAV's is good enough to provide rough initial approximation of camera positions but still accuracy of data is upto several meter level. The image block is already affected by an unknown 3D similarity transformation with respect to the reference therefore point cloud generated through this image block is also affected by the same. Generation process of point cloud from UAV images also contains random errors which decreases accuracy of UAV dataset. The mentioned effect of unknown transformation can be seen in fig.1.1, where ALS and UAV datasets are shown in green and red colour respectively whereas rotational affect can be seen in fig. 1.2. One can notice these shifts around building corners where UAV dataset is clearly shifted in one direction. Conventionally, this shift can be removed by direct sensor orientation (using precise on-board GPS and IMU) or indirect sensor orientation (using ground control points (GCP's)). These methods are considered reliable but are not cost-effective and require manual field work also.

Registration issue arises when acquired datasets are of same area having different characteristics and contains above mentioned shifts. Registration of overlapped 3D point cloud is major problem for applications in object modelling, 3D object recognition, 3D map construction, etc., (Liu, 2006). Principally, registration process of two point clouds is determination of best geometric transformation parameters that aligns one dataset closer to other (Xie et al., 2010). Significance of registration increases in manifolds when it comes to feature-based instead of using ground control information because of its low economic impact and can be executed at short notice. Features found in both datasets (overlapping areas) can be exploited for the purpose. An advantage of feature-based registration is that no target/control is required in scene and aimed at automatic feature extraction and matching (Bosché, 2012). Planar features are considered as most reliable features in 3D point cloud so conducted study focuses only on planar-based algorithms and exploits planar features existing in both datasets.

Several automatic and semi-automatic feature-based registration algorithms have been developed so far with different matching strategies. Matching strategies are influenced by characteristics of datasets and tries to optimally find true correspondences. Matching strategy deals with robust correspondence search

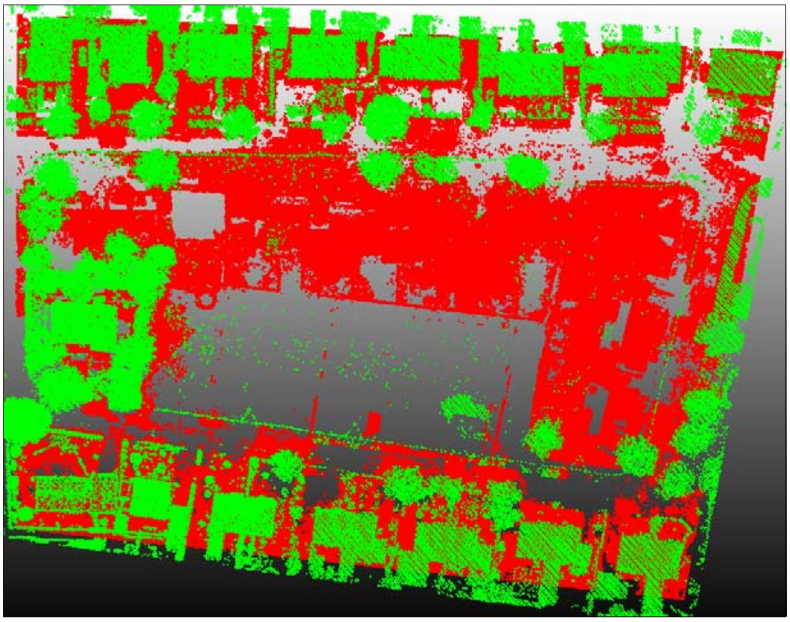


Figure 1.1: Illustration of both overlapping datasets in urban environment.
ALS dataset (green) & UAV dataset (red)

and comes up with true feature correspondences only. Conducted study is using dataset of an urban scene where plenty of planar features helps to optimize registration algorithm but also reduces chances of extracting true correspondences easily. Well-defined planar features seem more reliable for feature-based algorithms. Many authors have adopted different measures for robustness of matching strategy. Sharp et al. (2002) have described a fully automatic range image registration method that uses feature shape as a measure in conjunction with point positions without initial estimation but it is valid only for small scene. Dold and Brenner (2006), described a registration method, based on the extraction of planar patches in overlapping 3D laser scan data and used image information to improve it so is also dependent on extra information. An integrated approach have been used by Rabbani et al. (2007) for registration of point clouds by existing pre-hand knowledge about datasets. They have used a constraint based approach to reduce possible candidates of matching using this knowledge. This approach can also be utilized for this study as possible solution. Grant et al. (2012) have used pair-wise fine registration approach (point-to-plane) by formulating the general least square adjustment model but optimized only for planes and also not efficient when surface geometry is coarse. Gressin et al. (2013), described the optimization process of ICP based on the knowledge of feature shape and analyse these variations for linear, planar or volumetric features but lacking information about point extraction and adopted point-to-point strategy only without any modification in matching phase. Fast and robust matching could be achieved through effective features of interest especially in case of objects acquired with different point densities (Salvi et al., 2007).

This proposed research will be focused on extraction of planar features, their matching and registration. Reliable planar features will be selected and used to improve registration accuracy with redundancy found in both datasets by exploiting least square adjustment technique. A reliable matching algorithm will correctly extract planar features from both datasets, evaluate their correspondence and then exploit them for computation of transformation parameters. Accuracy of feature-based registration will be analysed by quantitative and qualitative statistical measures which will determine its reliability for being an alternate to conventional methods (direct or indirect sensor orientation). This analysis will be helpful to identify reliability of feature-based method for large photogrammetric blocks.

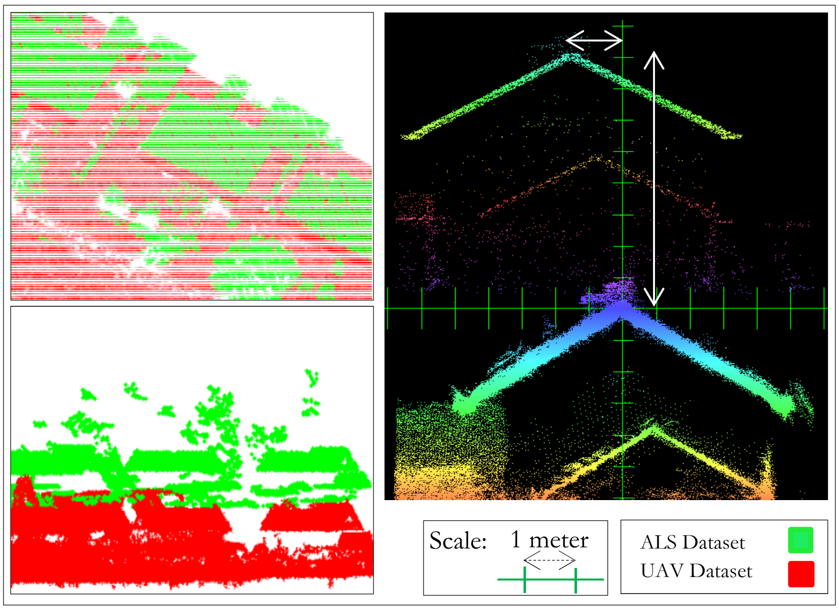


Figure 1.2: Illustration of horizontal & vertical shift found in both datasets

Discussed shifts are shown from perspective view in figure 1.2 where datasets are aligned to each other just few meters away. Point cloud mapper (PCM) has been used for this purpose. Datasets have shift of 2 meter and 8 meters in horizontal and vertical axis, respectively. However it can be observed that datasets are approximately well-aligned to each other in terms of rotation. Proposed study is to remove these shifts automatically developing a reliable matching strategy for true correspondence search and their exploitation for computation of transformation parameters. These transformation parameters will be used to register both datasets in order to make them reliable for photogrammetric applications. Different algorithms developed in the past for extraction of features in point cloud datasets will also be part of this research.

1.2. Research identification

UAV photogrammetric systems can be considered as cost-effective alternative to conventional photogrammetric techniques involved in data acquisition and production of different photogrammetric products e.g. Orthophoto, DSM, 3D point cloud, 3D mapping, etc.(Nex & Remondino, 2014). For 3D point cloud, laser scanning (airborne or terrestrial) is still basic important source of high precise 3D point data. However an emerging technique for generation of 3D point cloud data is execution of dense image matching technique using high resolution images acquired by UAV (Gerke, 2009). Registration of point cloud data from two different sources with different characteristics is of much importance in computer vision field e.g. 3D modelling, quality assessment, etc. This research is to register 3D point cloud generated by UAV's images with ALS dataset. Datasets are of same topographic urban scene but obtained in different time. This temporal shift may change structural detail found in both dataset and since study is about planar feature therefore it can have an impact on registration process.

In urban environment, large number of man-made structures exists which can easily be detected in point clouds due to their geometrical properties (roof planes). These planar features can also be used in feature-based algorithms for computation of transformation parameters. Extraction of true correspondence is problematic due to symmetrical geometries. Rabbani et al. (2007), have used a constraint based search approach to minimize possible number of candidates for being true correspondence using pre-hand knowledge about datasets. Dold and Brenner (2007), have also described a method for registration of terrestrial laser scans by applying an angular constraint based search approach.

Gressin et al. (2013), have assessed a method which computes robust geometric features on LiDAR point clouds in order to optimize the fine-registration algorithm ICP. Datasets (especially ALS) used by them is of different point densities and acquired in different times. In 'Matching' phase, they have used point-to-point approach without any variation and considered standard Euclidean distance. This adopted approach is sensitive with noisy datasets having inconsistent point density. UAV's image based point data also contains noise during its generation process. Therefore point-to-plane or plane-to-plane approach seems more reliable in order to deal with noise in UAV dataset. Other approaches like point-to-line, line-to-line, line-to-plane, plane-to-plane, etc. can also be analysed. Grant et al. (2012), have proposed a point-to-plane approach for registration of terrestrial laser scanned data by formulating least square adjustment model. It will also be assessed that how much this approach is effective in matching and overcome limitations of dataset.

Feature-based registration of UAV's image based point cloud with high precise ALS dataset has not been performed yet for solving 3D similarity transformation issues. Development of an automated registration algorithm for registration of UAV's image based point data (having low accuracy) with high precise ALS point data, which is independent of direct or indirect sensor orientation methods is main theme of this research. To summarize in one sentence, research identification is to confirm reliability of feature-based registration approach as trustworthy alternate to direct or indirect sensor orientation (costly and time consuming) methods.

1.2.1. Research Objectives

The main objective of purposed research is to develop a feature based registration algorithm between UAV's image based point cloud and ALS data. To reach this objective, few sub-objectives can be defined as:

1. To analyze plane-based feature matching approaches for reliable and robust registration.
2. To obtain optimal transformation parameters for both datasets and perform residual check to determine best approach.
3. To analyze statistically, validity of feature-based algorithm with conventional indirect sensor orientation method.

This research will use only planar features as observations for registration of UAV data with ALS data. By doing so, it is aimed to improve accuracy and quality of UAV's image based point data without using ground control information.

1.2.2. Research Questions

1. Which technique has been used for feature extraction and its reliability for registration?
2. Which kind of matching approaches are more robust for registration?
3. How far registration algorithm, reliably registers both datasets by using extracted/matched features?
4. How robust this approach will be when the scene (features) changed considerably between both datasets?

1.2.3. Innovation

Several works has been performed for registration of 3D point datasets using features especially in laser scanning environment. Point cloud generated through dense-image matching is modern technique and registration of point cloud with high precise ALS dataset for topographic scene is interesting to perform which is independent of direct or indirect sensor orientation (conventional methods). Innovation of this study is:

- ✓ Development of an automated algorithm which extracts features, validate their matching and utilize them for computation of transformation parameters.
- ✓ Prove reliability of feature-based registration technique against direct or indirect sensor orientation techniques.

1.3. Thesis Structure

A short but comprehensive introduction to summarize structure of presented thesis is given here.

Chapter 1 includes motivation, problem statement and research identifications. Described last section has been further divided into subsections i.e. research objectives, research questions and aimed innovation of this research. Chapter 2 provides theoretical and mathematical background involved in this proposed research. A broad review has been taken on existing methods and algorithms developed in past years for registration of point clouds in 3D environment. Review of feature-based algorithms for 3D data registrations is also included as final part of this chapter.

Chapter 3 includes description of pre-analysis of data and developed algorithm step by step. Pre-analysis/pre-processing of data consists of analyzing planar accuracy in both datasets by calculating distances from fitted plane through RANSAC. Different stages of algorithm are also discussed. Method includes automatic feature extraction from both point clouds, detection of true correspondences and finally providing final transformation parameters exist in both datasets. Plane-to-plane and point-to-plane registration methods are discussed in this chapter. Chapter 4 provides a brief overview of used datasets. Results obtained after implementation of developed algorithm are included with discussion on them.

Chapter 5 comprises of analysis part of conducted research. Performance of developed algorithm has been analyzed by adopted different statistical measures. Discussion on results before registration and after registration is also included in this chapter. Chapter 6 is last chapter of this study which includes final drawn conclusions, answers to research questions and recommendations for future study and development.

2. LITERATURE REVIEW

In this chapter, a brief review is given on different procedures/techniques involved in registration (feature-based) of 3D point clouds. In section 2.1, a short but comprehensive review about UAV photogrammetry is described. Section 2.2 is about procedures involved in point cloud generation through UAV images. Section 2.3 is about 3D data registration (coarse and fine registration aspects) and review about most standard ICP algorithm. Discussion about feature-based registration, feature extraction, transformation estimation and planar-based registration algorithms is included in section 2.4. Conclusion of chapter is given in section 2.5.

2.1. UAV Photogrammetry

Photogrammetry is generally defined as computation of metric measurements at aerial photographs about objects without having any physical contact with them (Ordóñez et al., 2010). Satellite, Aerial and terrestrial are termed as three major classification of photogrammetry. A sub-category of terrestrial photogrammetry where object size and camera-to-object distance both are less than 100m (330ft) and obtained images have convergent camera positions around the object is termed as close-range photogrammetry (Cooper & Robson, 1996). From last decade, another dimension of photogrammetry is emerging rapidly with its vast applications and is termed as unmanned aerial vehicle (UAV) photogrammetry. Kim et al. (2013), have defined UAV photogrammetry as combination of aerial and terrestrial photogrammetry, which is being applied over short distances. Unmanned aerial vehicles have many platforms e.g. fixed-wing, mini-helicopter, multi-copter, etc. They become UAV photogrammetric systems when cameras/sensors are attached with them for remote-sensing purposes. Their evolution driven primarily by military users, and then by civilian users for earth sensing reconnaissance and scientific data collection for multi-purpose applications (Wallace et al., 2012). Remondino et al. (2011), have discussed UAV's role with many applications e.g. agriculture, cultural heritage, 3D reconstruction, surveying, monitoring, etc. UAV photogrammetry is more efficient than traditional photogrammetric aerial flights for limited areas in order to reduce the cost and production of suitable large scale images (Chiabrando et al., 2011).

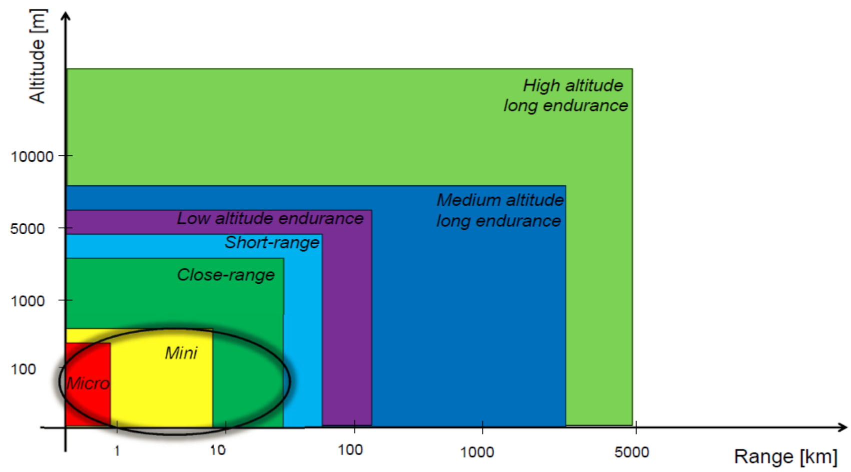


Figure 2.1: UAV overview (van Blyenburgh, 1999)

An overview of UAV's was presented by van Blyenburgh (1999) (president of the European unmanned vehicle systems association 'EURO UVS'). He termed UAV's as un-inhabited aerial vehicle, described their specifications and wrote about commercial aspects of UAV's. In recent times, it becomes quite general that UAV's are being used by local authorities/commercial users within a range of <15 km having an altitude <100 m. Elliptical imprint in figure 2.1 specifies usage of UAV's for small scale/civilian purposes.

UAV photogrammetry is extremely proving itself as helpful tool in aerial photography, surveillance, live video monitoring, security services, search & rescue, mapping services, crop monitoring, wild-life protection, etc. Their cost-effectiveness and easy-handling has motivated researchers to exploit them in different fields for their applications. Few applications of UAV's are landslides investigations (Niethammer et al., 2012), measurement of building facades (Ordóñez et al., 2010), photogrammetric surveys in archaeological sites (Chiabrando et al., 2011), crops monitoring (Zarco-Tejada et al., 2013), etc. Besides using off-the-shelf cameras, Kim et al. (2013) have made use of smart phones with conclusion that smart phones are not only suitable for UAV systems but can also be used for photogrammetric products depending upon their application. Modern UAV photogrammetric systems are also using different sensors other than cameras e.g., Wallace et al. (2012) have developed a UAV-LiDAR system having an application to forest inventory. These applications are evident that UAV photogrammetry is playing an eminent role for development of various photogrammetric applications and has potential to create new fields of research in remote-sensing community.

2.2. 3D Point Cloud

Airborne laser scanning (ALS) is a well-known and well-matured technique for collection of point data over topographic terrains for different applications. For large scale topographic areas, Lidar system delivers 3D point cloud data which contains large number (in billions) of points having precise positional accuracy (Vosselman & Mass, 2010). In this literature review, 3D point cloud extraction from collected UAV imagery is discussed only.

Among many other applications, one of the important applications of UAV photogrammetric system is to capture high resolution images over targeted area. Detailed imagery captured from UAV can produce dense point clouds using multi-view stereopsis (MVS) techniques combining photogrammetry and computer vision (Harwin & Lucieer, 2012). Orientation of images is initial step after their acquisition through UAV photogrammetric systems. UAV images having more than 60% overlapping are highly recommended for point cloud extraction through them. Structure from motion (SfM) is an automated method for creation of static scene from sequence of images and resulting in individual camera orientations and 3D point clouds (Westoby et al., 2012). They have described purpose of this method as estimation of extrinsic parameters of camera (camera position) by exploiting epipolar geometry of corresponding features. It exploits corresponding feature points found in overlapping images as tie points to connect them and orientate them without having any prior information about extrinsic parameters of camera.

Keypoints and descriptors are tracked along epipolar line between stereo images for finding corresponding features. Traditional area based matching techniques (2D search) results in too many false matches due to pixel similarity in both images. Lowe (2004), has explained a technique named as 'scale invariant feature transform' (SIFT) for finding corresponding features. Selected corner point (a point having strong gradients) will be searched for its correspondence in its stereo mate on basis of gradient histograms. After this step, whole image block has to be adjusted through these retrieved corner points (descriptors) which served as tie points between images. This block adjustment can also results in sparse point cloud. For dense point cloud, patch-based multi-view stereo (PMVS) or semi-global matching (SGM) can be executed. Dense image matching results in dense point cloud data by exploiting forward intersection of maximum corresponding feature points in object space (Gerke, 2009). Semi-Global matching (SGM) developed by Hirschmuller (2008), is an optimized technique used for this purpose. Matching is done only in stereo image pair for creation of point cloud data and do not exploits redundancy of matched points in multiple images. Furukawa and Ponce (2010), have also developed a method named as patch-based multi-view stereopsis (PMVS). Initially they match corner features in multiple images and obtain more accurate geometry through redundancy. These initial patches are then expanded through area based matching. Point cloud obtained by this method is not denser than SGM but has much better accuracy.

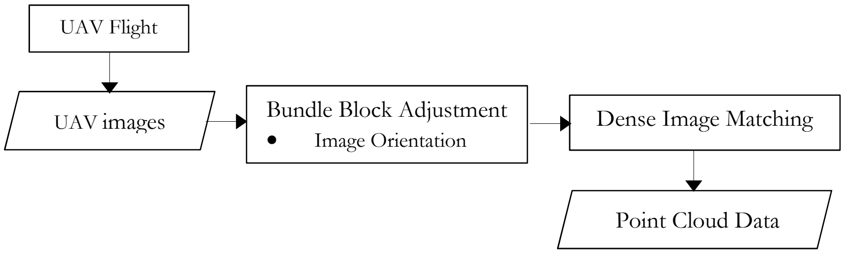


Figure 2.2: Point cloud generation process using UAV images

2.2.1. Image-based Point Cloud Density

Point cloud generated by using high resolution UAV images has varying point density. Maximum number of corresponding points exploited during dense image matching results in dense point cloud data. High resolution UAV images have an impact on point density because chances of correct correspondences from paired images increases. Large number of mismatched pixels exists in images (due to occlusion, surface properties, etc.) which introduces certain noise level in generated point cloud, however structures are well preserved in image-based point cloud (Gerke, 2009). Potential areas for incorrect matching are those areas which have low texture, reflecting surfaces, vegetation, etc. (Haala & Rothermel, 2012) and due to their properties it also have an effect on density of point cloud.

Several types of features exist in topographic scene having different properties. These properties include shape, size, volume, slope, flatness, scattering, content, texture, etc. Due to these properties, matching points varies from object to object and results in irregular point density. Usually for planar features/structured features having some contrast, point density is quite dense because large number of correspondences are extracted from them. Another important factor which can affect point density is occlusion found in UAV images. Occlusions appeared in images can result in point cloud having more empty spaces (mismatched pixels). Short base image configuration is always recommended with nadir view of area to avoid occlusion. Above described factors are responsible for noisy (denser) point cloud generated by use of images taken by UAV photogrammetric system.

2.3. 3D Point Cloud Registration

In ALS case, point data is captured using sophisticated methods and equipment resulting precise and smooth 3D point data. In UAV case, high resolution images are used for creation of 3D point dataset by applying modern developed techniques. Due to payload limits for UAV photogrammetric systems, high precise GPS and IMU cannot be mounted on them. However, using micro GPS for these systems enables us to have a rough initial approximation of camera positions. These approximated positions bring an unknown shift (in terms of position and scale) in whole image block and therefore photogrammetric product (point cloud) generated from it contains positional error and scale deformation also. Conventionally, shift can be removed by direct sensor orientation (using precise on-board GPS and IMU) or indirect sensor orientation (using ground control points (GCP's)).

Registration of 3D point datasets can be described as process of alignment of two datasets from two different locations. Datasets acquired with two different techniques also differ in their characteristics e.g. ALS dataset and UAV image based dataset. Registration of overlapped 3D point cloud is major problem for applications in object modelling, 3D object recognition, 3D map construction, etc., (Liu, 2006). Principally, registration process of two point clouds is determination of best geometric transformation parameters that aligns one dataset closer to other (Xie et al., 2010).

2.3.1. Coarse & Fine Registration

Generally 3D data registration comprises of two steps (Bosché, 2012):

1. Coarse/rough registration (to align datasets roughly), followed by
2. Fine registration (to align datasets optimally)

According to Gressin et al. (2013), registration algorithms for 3D data can be classified into three types depending on application. These three types are feature-based, surface-based (model) and point-based. Dold and Brenner (2007), has described coarse registration as estimation of relative transformation parameters between two independently acquired datasets without having any knowledge about their orientation beforehand. Coarse registration brings two datasets more close than earlier one but this registration is not optimal. For optimal registration, fine registration has to be done after coarse/rough registration. However, it is true that fine registration generates optimal results but its convergence is dependent on obtained results through coarse registration (Bosché, 2012). For automated matching, features (point, linear, planar, and volumetric) which exist in overlapping region of datasets are helpful for initial/coarse registration.

2.3.2. Iterative Closest Point (ICP)

After coarse registration, fine registration can be achieved through well-known algorithm Iterative Closest Point (ICP) developed in early 90's by Besl and McKay (1992). This method was initially proposed for registration of 3D shapes based on point-to-point correspondences which requires correct initial orientation parameters and is also not good in handling outliers (noise). With the passage of time, different ICP variants have been evolved with much great improvement in convergence and accuracy. First and initial improvement in ICP was made by Chen and Medioni (1992), by exploiting point-to-plane correspondences instead of point-to-point. These two algorithms are considered as standard ICP algorithm for 3D data registration. Few variants/improvements carried out on ICP are discussed in following paragraph.

Sharp et al. (2002), have explained an automated method describing the influence of invariant features and their position in order to simplification of ICP algorithm especially in the presence of noise in dataset. Least squares matching of overlapping surfaces for automatic co-registration of point clouds have been described by Gruen and Akca (2005), by minimizing sum of squares of the Euclidean distances between surfaces. Their method is convenient to handle datasets having differences in resolution, scale, time, etc. Rusinkiewicz and Levoy (2001), classified several variants of ICP and evaluated their effect on the speed in order to obtain accurate alignment. Salvi et al. (2007), have given an excellent overview of classification of registration methods. They classified registration algorithms into coarse and fine registration and analyzed them on the basis of different criteria i.e., features exploited, registration strategy, motion estimation, robustness, etc. According to them, for coarse registration, method of Chu-Song et al. (1998) is considered as best in presence of low resolution views, principal component analysis is optimal when computing time is critical and genetic algorithm is most robust with noise but is expensive in time. For fine registration, standard ICP method developed by Chen and Medioni (1992) has been considered most competent algorithm which performs also well with non-overlapping regions. Grant et al. (2012), have described a pairwise fine registration approach utilizing corresponding point and plane feature, along with their stochastic properties. They defined optimum registration parameters by formulating least squares adjustment model and compared them with standard ICP algorithm. Gressin et al. (2013), have also evaluated this method by taking neighborhood shape and its reliability into account and improve two steps (selection & rejection) of ICP. They optimized ICP for registration of point clouds having different point densities acquired in different time over same area in order to find change detection.

3D point cloud data collected by airborne laser scanning and generated by UAV imagery, both are of different properties having unknown transformation shift between them. Registration of both datasets can minimize/remove these shifts. ICP algorithm having point-to-point matching strategy is not enough robust for noisy datasets and point-to-tangent plane matching strategy provides much better registration accuracy (Akca, 2007). UAV point dataset is generated through images and contains lot of noise in it. In presence of noisy dataset it seems feasible to apply point-to-plane strategy. Existing features in topographic dataset might be helpful for registration of both datasets. Following section describes 3D point data registration carried out by using extracted reliable features found in both datasets.

2.4. Feature-based Registration

Point cloud data of an urban scene contains large number of features which can be exploited in feature-based algorithms for datasets registration. Feature type can be defined according to their geometrical characteristics and it can be point, line, planes, circular shapes, cylinders, torus, etc. Feature based algorithms exploits different type of features found in datasets to estimate transformation parameters. According to Bendels et al. (2004), feature definition, their way of matching and their exploitation for computation of transformation parameters are important for any feature-based algorithm. Feature-based algorithms align datasets through the correspondence of feature primitives exist in both datasets (Gressin et al., 2013). These features can be key points (Stamos & Leordeanu, 2003), segments and curves (Stein & Medioni, 1992), local planes (Dold & Brenner, 2006), spheres/cylinders (Frome et al., 2004).

Extraction of features and computing transformation parameters by exploiting these features are termed as two important steps of feature-based registration. Classical methods of registration make use of sign marks, ground marks, pointers, etc., in order to achieve data registration. 3D positions of these signs are then utilized in process of transformation for registration. This technique is robust and accurate for data registration but demands huge effort and expensive in time also. Usage of signalised points/artificial markers also add an extra layer of uncertainty and error in registration process (Bosché, 2012).

Drawback of above described classical methods have motivated researchers to search for an automatic registration of datasets independent of any artificial targets to be placed in object space. Feature-based registration has another advantage that they do not require initial estimates of rigid-motion parameters (Chu-Song et al., 1999). Several algorithms have been developed so far for registration which exploits existing information available within dataset. Conducted study is only about planar features therefore discussion about only plane-based algorithms is briefly described in following subsection.

2.4.1. Feature Extraction

In an urban environment dataset, planar features are found excessively all over the area. This excess of existence makes it easy for their extraction. For plane-based matching, extraction of planar surfaces from both datasets is regarded as an initial step. Large number of algorithms exist for their extraction e.g., through region growing process exploiting Bayesian framework (Osorio et al., 2005), segmentation method (Hoover et al., 1996), clustering technique (Vosselman, 1999), gradient-based range image segmentation method (Gorte, 2007), Hough transform (Vosselman. et al., 2004), RANSAC for shape detection (Schnabel et al., 2007).

RANdom SAmple Consensus (RANSAC) is well-known algorithm for shape detection and has large application variability in various fields of computer vision. Initially proposed by Fischler and Bolles (1981) for model fitting with applications to image analysis and later on devised by many other authors for various applications. RANSAC can be used for model fitting, shape detection, outlier removals, etc. but most prominent motivation to use this technique is its robustness with noisy datasets (Vosselman & Mass, 2010). After process of surface growing/segmentation, planarity of a segment is not sure certain and it contains outliers, e.g. points on trees, walls, other surfaces which are not part of same roof. (Sande et al., 2010). To deal with these outliers, robust plane-fitting approach through RANSAC is recommended for datasets having noise in them. Therefore it is concluded that RANSAC based plane-fitting approach is helpful in handling noisy datasets like UAV point dataset.

2.4.2. Transformation estimation

After completion of correspondence matching in target dataset, these planar features are used as observations for estimation of transformation parameters. Seven parameters are needed for transformation between 3D point clouds having homogeneous coordinates. These seven parameters are 3 rotations $(\omega, \varphi, \kappa)$, 3 translations (τ_x, τ_y, τ_z) and 1 scale(s). Scale parameter is considered as 1 if there is no deformation in feature shape but if scale change in both dataset or shape deformation happens than it is needed to be considered. Theoretically non-rigid transformation (similarity transformation) can be obtained using equation:

$$\boldsymbol{Transformed\ Points} = \boldsymbol{Scale} \times (\boldsymbol{Rotation} \times \boldsymbol{Points}) + \boldsymbol{Translation} \tag{2.1}$$

Mathematically, rotation angle matrix (3×3) and translation vector are described as:

$$\text{Rotation matrix } (R) = \begin{bmatrix} r_{xx} & r_{xy} & r_{xz} \\ r_{yx} & r_{yy} & r_{yz} \\ r_{zx} & r_{zy} & r_{zz} \end{bmatrix}, \text{ translation vector } (T) = \begin{bmatrix} \tau_x \\ \tau_y \\ \tau_z \end{bmatrix}, \forall \quad x = 1, y = 2, z = 3$$

Rotational parameters can be calculated as followings:

$$\left.\begin{aligned} \omega &= \tan^{-1}(-r_{zy}/r_{zz}) \\ \varphi &= \tan^{-1}\left(r_{zx}/\sqrt{r_{zy}^2 + r_{zz}^2}\right) \\ \kappa &= \tan^{-1}(-r_{yx}/r_{xx}) \end{aligned}\right\} \tag{2.2}$$

K Khoshelham and Gorte (2009), have described a plane-based transformation model for estimation of transformation parameters as:

$$a_{(4\times n)} = \mathbf{H}_{(4\times 4)} \times b_{(4\times n)} \tag{2.3}$$

The term 'n' is number of points/planes to be used in model and 'H' is a 4×4 similarity transformation matrix. Minimum three corresponding planes from both datasets are required to form a set of equations for computation of H. This model can be expressed in matrix form as:

$$\begin{bmatrix} a_x \\ a_y \\ a_z \\ d_a \end{bmatrix} = \left[\begin{array}{ccc:c} r_{xx} & r_{xy} & r_{xz} & \tau_x \\ r_{yx} & r_{yy} & r_{yz} & \tau_y \\ r_{zx} & r_{xy} & r_{zz} & \tau_z \\ \hdashline 0 & 0 & 0 & S \end{array}\right] \begin{bmatrix} b_x \\ b_y \\ b_z \\ d_b \end{bmatrix} \tag{2.4}$$

$[a_x, a_y, a_z, d_a]^T$ and $[b_x, b_y, b_z, d_b]^T$ are the normal vectors and distance parameter of planes found in both datasets. A set of linear equations will be acquired and after some rearrangements transformation matrix 'H' can be estimated for R and T. Linear equations are obtained therefore initial values are not required and results will be achieved in single iteration. Results obtained (R & T) through this estimation may not be accurate and have a chance to be effected by wrong correspondences between both datasets. Redundancy of possible matches can overcome this problem and make its convergence feasible.

2.4.3. Plane-based Algorithms

Planar features are reliable features and helpful for registration of topographic point datasets Planar features have been used by Dold and Brenner (2007) in their algorithm for automatic coarse registration. Planar features are extracted through region growing segmentation and used to compute initial values of transformation parameters automatically for datasets acquired independently. Along with plane features, angle constraints are also used to determine correspondences. To eliminate wrong correspondences, they put a criteria of relative angles exist between normal vectors of plane triples constructed in each scan or in other words corresponding plane triples are extracted by using these angle constraints. They have set matching constraint as 1^0 for normal vector deviation and 1m for distance from origin. Pair combinations which retrieve most of correspondences with these constraints are declared as correct pairs. Dold and Brenner (2006), also present an image based registration algorithm with range data based on planar surfaces (Fig 2.3). Laser scanners are mostly equipped with high resolution image sensors therefore information extracted from images can also be exploited for improvement of registration process. In their algorithm, they extract corresponding planar surfaces in two overlapping scan positions and also extract planar surfaces from images. Correlation between corresponding planar patches of range data and image data has been calculated and exploited in improvement of registration process.

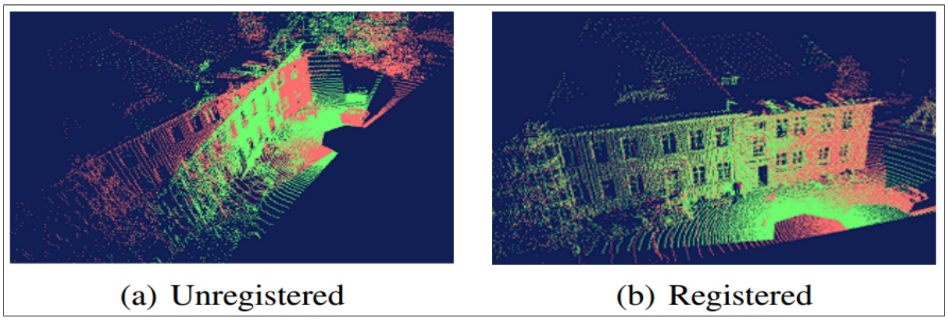


Figure 2.3: Result of registration using planar surfaces (Dold & Brenner, 2006)

A semi-automated plane-based algorithm for coarse registration has been proposed by Bosché (2012). In his algorithm, registration process is decomposed into three stages by two assumptions about datasets. First assumption is about conversion of 3D model objects into meshes and other is about orientation of both datasets along z-axis. In first step of registration, vertical and horizontal planes exist in both dataset are extracted using RANSAC. After extraction of planes, model and point cloud are aligned in x-y plane by two correct correspondences of non-parallel planes. In last step, datasets are aligned in z-direction (translation) by using one correct correspondence.

Rabbani and van den Heuvel (2005), have proposed an automated method correspondence search for registration of point clouds in industrial scenes. Their approach is based on detection of planes and cylinder exists in the area. For automatic correspondence search of features, they exploited geometric constraints applied on initial correspondences to refine/confirm their matching. Initial matches have been found on basis of some weak measures like size, point density, etc. and no constraints have been fixed. This made all initial correspondences equally valid. In second step, rotation component of initial matches has been figured out by applying geometric constraints on them. These constraints ensure that rotation must be around normal axis (normals aligned after initial match remains same) and translation is only for planar movement in plane. In third and last step, rotation obtained from second step has been fixed and correspondences are found by looking at similarity of their normal directions (parallel planes have almost same normal directions). In result of these three steps, correct correspondences of objects have been found and used in point cloud registration.

Stamos and Leordeanu (2003), have made use of linear and planar features for pair wise registration between datasets. Their algorithm initiates with segmentation process and converts 3D range data into set of bounded planes and finite lines. Boundary of planes and dimension of lines (start point, end point, etc.) are also extracted. Lines lying on bounded planes are used for parameter estimation. 3D dataset consists of many lines and invalid lines are first removed by applying appropriate threshold value which has to be determined during pre-processing step. Valid line pairs are ordered and used for parameter estimation one by one. Estimated R is applied to all pairs and rotated lines whose directions and respective plane normal do not fulfil a fixed threshold are removed. Similarly other pairs of lines are also declared invalid who have same behaviour with estimated T. Remaining lines are then exploited for computation of R and T again. These transformations are than ordered by number of valid pairs used by them and higher grade has been given to higher number of matches. Finally R and T are computed by set with higher matches (high graded transformation set).

2.5. Conclusion

Applications of collected data through UAV photogrammetric systems are growing day by day with different dimensions. Modern techniques have made it possible to generate 3D point cloud data from imagery attained by UAV's and are discussed in detail. Feature-based registration (independent of GCP's) of generated point cloud with any other 3D point cloud having better accuracy is termed as effective way to increase its own accuracy also. It becomes more interesting when registration aimed to be automatic rather manual. Algorithms developed in past 20 years involved in 3D data registration have been discussed. RANSAC based plane fitting approach has been found more robust in case of noisy datasets. Discussed algorithms have achieved coarse and fine registration of 3D range data using several matching strategies by exploiting existed features in their datasets. A review on fine registration through ICP algorithm has also been narrated. According to many researchers, point-to-plane matching strategy is considered as more effective instead of point-to-point strategy especially dealing with noisy datasets. Effectiveness of plane-based matching provokes idea about feature-based matching. One of important objective of this research is to analyse which matching approach (plane-to-plane or point-to-plane) and how far it is effective to register UAV's data with precise ALS data.

3. RESEARCH METHODOLOGY

This chapter briefly explains adopted methodology to carry out this research in order to achieve final results. Section 3.1 describes overview of proposed study and general workflow. Pre-processing and pre-analysis of data are explained in section 3.2. RANSAC application for plane extraction is discussed in section 3.3. Brief description about feature correspondence search plan is described in section 3.4. Evaluation of obtained correspondences is also discussed in section 3.4. In section 3.5., registration process of datasets is explained and concluding remarks based on discussion of adopted algorithm are incorporated in section 3.6.

3.1. Overview

Feature-based registration of two datasets (point cloud) is core theme of this study. Plenty of features can be found and extracted in point datasets but most reliable and common features are planar features. In case of urban environment, due to constructive areas/accommodation structures, probability of finding planar features certainly increases. Examples of planes that can be found in such scene are roof planes of buildings, open ground planar areas, long vehicles upper surface (temporary objects), etc. This excess of plane existence is advantageous and problematic at same time for registration of both datasets. Sure existence and extraction of planar features makes it advantageous, while search of true correspondences in presence of similar geometry/symmetrical planes makes it problematic. Important part of this study is to devise such an automatic correspondence search plan which can itself detects possible candidates for matching and decide also about their being true or false. Workflow for proposed methodology is shown in figure 3.1 and discussed in following paragraph.

Data preparation is considered as initial step and its output will be taken as input for feature based matching. Most important step of algorithm is development of correspondence search plan/feature matching strategy from target dataset (UAV dataset). Registration of datasets will be performed after finding true correspondences from developed search plan and transformation parameters will be calculated. Some parts of algorithm (fig. 3.1) are described briefly in subsequent sections of this chapter.

3.2. Data Preparation (Pre-Analysis & Pre-Processing)

Preparation of data is considered as important step for registration of datasets. It will provide us key information about features found in datasets and this information will be exploited in further processes. For this proposed study, data preparation is composed of two major steps: Data pre-analysis and Data pre-processing. A flowchart of data preparation process is displayed in figure 3.2 and involved both steps are further discussed in following paragraphs.

<u>Pre-Analysis</u>:

Data pre-analysis is termed as procedure to extract important information about accuracy of planar features found in both datasets. RANSAC based plane-fitting approach is applied to both datasets and obtains distance values from the fitted plane. Error tolerance (threshold) value required for consensus set fitted by RANSAC algorithm is needed to fit a plane. This value is noted down when normal distribution for distance form fitted plane is achieved for both datasets.

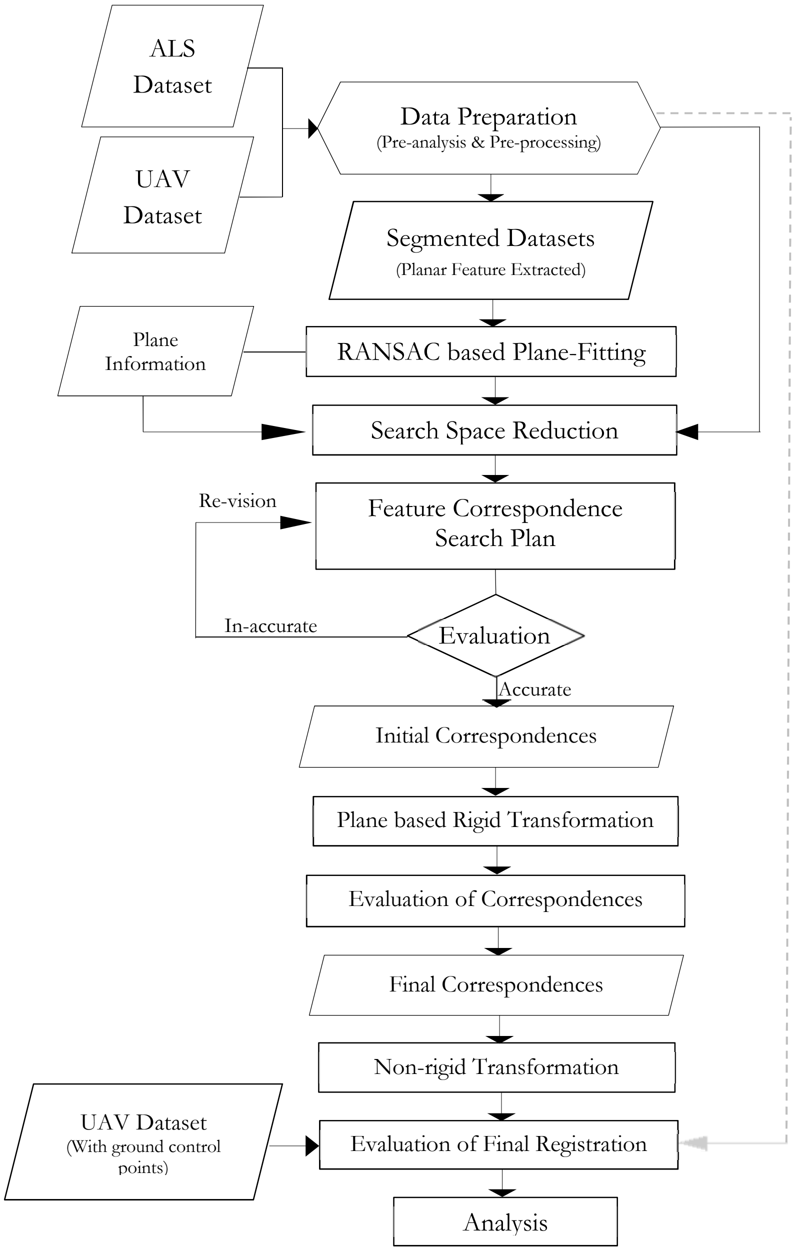


Figure 3.1: General Process of Feature based Registration between ALS and UAV datasets

<u>Pre-processing</u>:

After pre-analysis of data, next step is data pre-processing. This step is further divided into two steps: Filtering and Surface growing/segmentation. ALS and UAV datasets are of urban environment, therefore both datasets contains several uncovered ground objects/areas and some of them are also planar e.g. crops field areas, road surfaces, play grounds, parking areas, vehicles (temporary objects), tiny vegetation, etc. Theoretically these planar surfaces can also be used for registration purposes but proposed study focuses only on roof planar surfaces. These features may become problematic during search of true correspondences. To reduce search space, all these objects/areas can be eliminated from dataset. A reasonable approach is to remove all these objects from both datasets and removal process is termed as filtering (Vosselman & Mass, 2010). Several methods have been developed so far for process of filtering the point cloud datasets. Mathematical morphological filtering (Haralick et al., 1987), slope based filtering (Vosselman, 2000) and progressive densification (Axelsson, 2000) are some of well-known algorithms developed for process of filtering. M. Gerke and Xiao (2014), have used commercial software LAStools component 'lasground' (Axelsson, 1999) for classification of Lidar data into ground and off-ground data. Filtering both datasets will remove some temporary/useless/problematic objects from them.

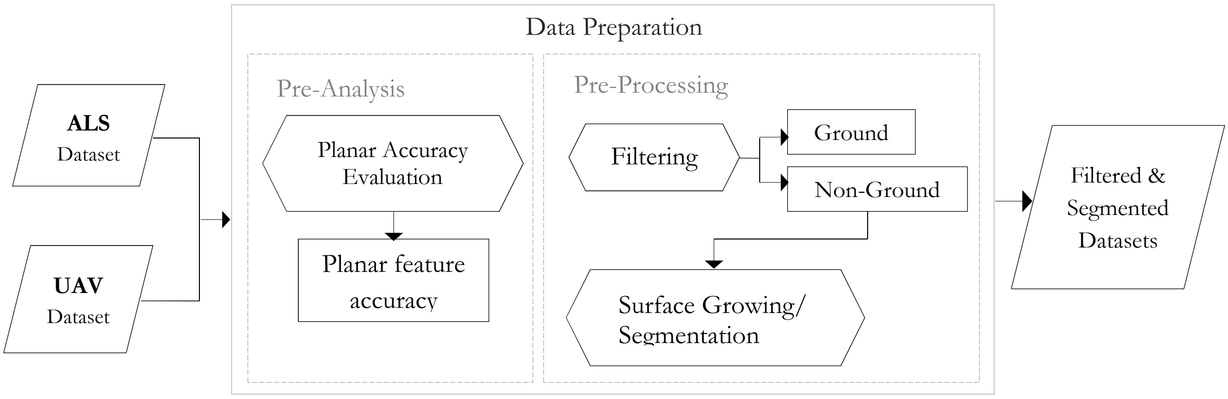


Figure 3.2: Data Preparation Process

Surface growing/Segmentation of point cloud data is executed for feature extraction and is performed by clustering all points of same cluster applying some conditions (Vosselman & Mass, 2010). In other words, points having same characteristics e.g. smoothness, same normal direction, etc., have been grouped together and provides information about features exist in datasets. Many algorithms exist for feature extraction e.g. detection of planes in3D point cloud by Hough transform (Maas & Vosselman, 1999), plane detection by RANSAC proposed by Schnabel et al.,(2007), region growing by Vosselman. et al. (2004), etc. Planar accuracy results found in pre-analysis of datasets will be used for setting up suitable parameters for surface growing algorithm. These parameters are used compute planar shapes during surface growing process. Planar features especially building roof planes are most suitable/appropriate features in point data to be preserved. Therefore, special attention will be given to planar features for their exploitation in data registration.

Outcome of data preparation is taken as input for next processes and values obtained in this process are extremely helpful during plane-fitting through RANSAC for computation of plane parameters. Therefore, quality of data preparation can play an effective role in selection of suitable and well-defined features.

3.3. RANdom SAmple Consensus (RANSAC) based Plane-Fitting

RANSAC can be used for model fitting, shape detection, outlier removals, etc. but most prominent motivation to use this technique is its robustness with noisy datasets (Vosselman & Mass, 2010). After implementation of surface growing, extracted segments are not completely coplanar and contain outliers, e.g. points on trees, walls, other surfaces which are not part of same roof (Sande et al., 2010). To deal with these outliers, robust plane-fitting approach through RANSAC has to be applied for both segmented datasets.

Plane-fitting through RANSAC is extremely helpful when applied to UAV dataset as it contains more noise than ALS dataset. Due to noise in UAV dataset, probability of outlier increases for each segment after segmentation, therefore this technique is much more helpful for UAV dataset. For each consensus set (critical part of RANSAC), an error tolerance has needed to be set for plane-fitting of each segment (fig. 3.3). Computation of error tolerance has been discussed in detail by Bae and Lichti (2008). Determination of a segment point as an inlier or an outlier is also an output of RANSAC algorithm but an appropriate threshold value (error tolerance value) must be selected for this purpose. This value can be selected by using beforehand knowledge about the datasets. Inliers/outliers ratio has been selected on the basis of this threshold value (Bae & Lichti, 2008). Therefore, values obtained during planarity accuracy evaluation and adopted for segmentation process are set as a threshold value for plane-fitting.

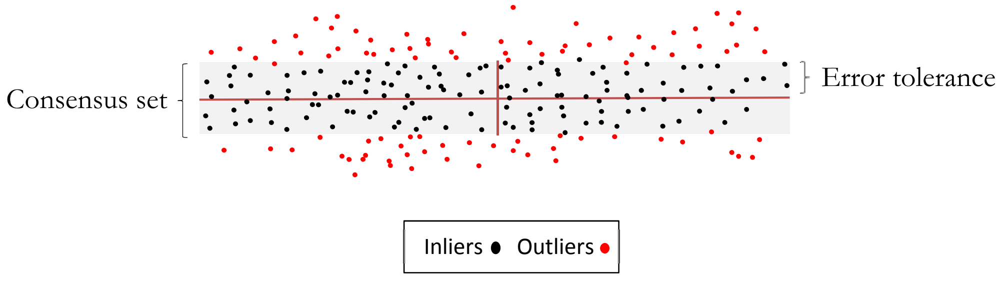


Figure 3.3: RANSAC principle

Mathematically, a plane can be well defined by its parameters .i.e. normal vector and perpendicular distance from origin.

$$ax + by + cz + d = 0 \tag{3.1}$$

Where **a**, **b**, **c** and **d** are plane parameters. **a**, **b** and **c** are components of plane normal and are obtained by applying Principal Component Analysis (PCA) to points (inliers) contained by consensus set during RANSAC algorithm. Normal of surface is axis of minimum variation which is last principle component of PCA or in simple words eigenvector of smallest eigenvalue provides good approximation about plane normal. Eigen values and Eigen vectors are used here for determination of principle components.(Sande et al., 2010). **d** is perpendicular distance from origin and since plane is an infinite surface in space so its value is dependent on direction of plane while normal vector determine the direction of plane. Along with basic plane parameters, secondary information can also be extracted during plane-fitting. This information includes planar segment density (number of points per plane), angle differences, mean (centre of plane), inliers & outliers ratio, etc. All these informations are exploited later on in correspondence search plan.

3.3.1. Sensitivity of plane parameter '**d**' with RANSAC

Perpendicular distance '**d**' from origin is fourth parameter of a plane. Geometrically, value of this parameter is dependent on surface normal direction and a slight shift can destabilize its value. This slight shift in normal direction does not have any major impact if plane is near to origin. However, if plane is situated far away from origin, a very little shift even matters then. Due to this behaviour, '**d**' is much more sensitive with RANSAC algorithm when large distance exists between origin and datasets. RANSAC uses random sampling of given points to form its consensus set and normal found for that set has always a little change in it for each run. This small alteration of normal value causes a large difference in '**d**' each time and different parameter have been achieved. Gravity of this effect increases manifolds if RANSAC has to deal with noisy datasets (UAV dataset). If this value of '**d**' is used for computation of transformation parameters, numerical instability occurs and wrong results will be achieved. To avoid this or to overcome this effect, normalization of datasets takes place and translational shifts are applied to datasets in order to minimize distance between origin and dataset.

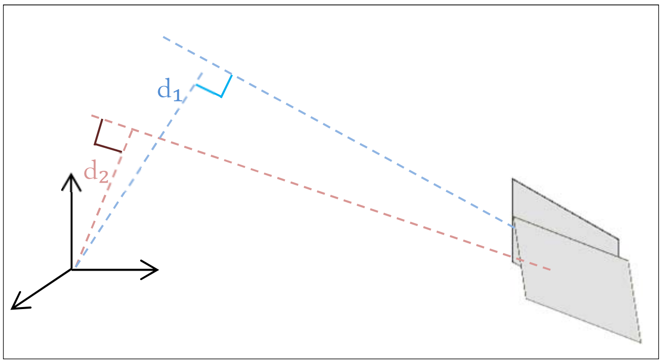


Figure 3.4: Effect of RANSAC on plane parameter 'd'

3.4. Feature Correspondence Search Plan

Topographic point datasets contains large number of planar features in them. Other features like point, linear, torus, spheres, etc. do also exist but most interested/reliable features are flat surfaces/planar features for this study. Availability of planar features in excess makes it easier for their detection/extraction but obstruct also from detection of true correspondences. Measures adopted for correspondence search plan and their why (motivation) and how (methodology) are also described here in detail. Influential or decisive measures which have been adopted are Euclidean distances, segment density, outlier ratio, and normal angle difference. Feature correspondence search plan is aimed to automatically detect, extract and evaluate correspondences on basis of above described measures and results obtained from them.

3.4.1. Search Space Reduction

As discussed earlier in chapter 2 that UAV photogrammetric systems are equipped with a micro GPS on them and data obtained from them has translational, rotational and vertical shift in it. However, collected data is just a few meters away from real positioning (fig.1.2). This pre-knowledge about datasets makes it somehow reasonable to put some realistic constraints for actual correspondence search. This approach seems practical to reduce possible number of correspondences in target dataset by adopting some suitable constraints/threshold values based on available pre-hand knowledge about both datasets. This kind of constraint based approach to limit number of possible correspondences in search space has been presented by Rabbani et al. (2007).

Reduction of search space can be considered as initial step towards finding true correspondence from target dataset (UAV dataset). Search space can be reduced by adopting some measures and adopted measures are distance, normal angle deviation, segment size (point density per plane) and outlier ratio. All these measures are discussed in detail in following paragraphs;

- <u>Distance between planes</u>:
  Both datasets are already coarsely aligned to each other and translation & vertical shift exist between them is only few meters. With this approximation, distance between each segment of both dataset can play role as an initial measure to figure out possible correspondences in close neighborhood. Distance can be calculated between them by two ways i.e. Euclidean distance and perpendicular distance. Both nature of distances have different repercussions and are discussed hereunder;

<u>Euclidean Distance:</u> Euclidean distance (fig. 3.5(a)) can be calculated from center of one plane to center of other plane exist in other dataset. Since both datasets are geo-referenced, therefore simple calculation is made by using following formula;

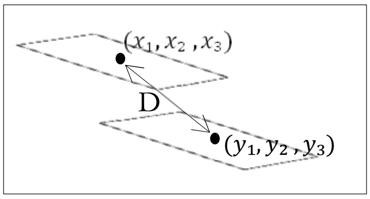


Figure 3.5(a): Euclidean distance

$$D = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2} \quad (3.2)$$

<u>Perpendicular Distance:</u> Perpendicular distance (fig. 3.5(b)) can be calculated by taking dot product between normal vector of one plane and vector connecting two centers. It is defined as projected distance exists between two centers. Let $X(x_{1,}x_{2,}x_3)$ and $Y(y_{1,}y_{2,}y_3)$ be center point of ALS and UAV planes, respectively and $\hat{n}\,(a, b, c)$ is normal vector of planes. Their projected distance can be calculated as;

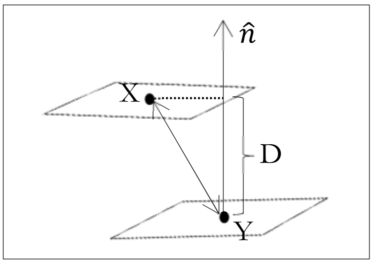


Figure 3.5(b): Perpendicular distance

$$D = \frac{|(\overline{XY}).\hat{n}|}{|<\hat{n}>|} \quad (3.3)$$

$$D = \frac{|a(x_1 - y_1) + b(x_2 - y_2) + c(x_3 - y_3)|}{\sqrt{a^2 + b^2 + c^2}} \quad (3.4)$$ (Anton & Chris, 2005)

Above described both forms of distances can be used but both results in different correspondences. Correspondences obtained by exploitation of perpendicular distance are not reliable because there might be many planes in close neighborhood which are parallel to each other but are not true correspondences. Due to symmetrical geometrical features existence in close neighborhood selection of minimum perpendicular distance criteria can leads to wrong correspondences. Since both datasets are already just few meters apart, therefore perpendicular distance increases more chances for selection of wrong corresponding segments. Another issue to negate perpendicular distance values is existence of too many parallel planes in whole target dataset and minimum value of this distance can result in wrong corresponding plane which lies far away from source plane. For initial guess to determine correspondences, it seems feasible to calculate Euclidean distances between segment centers instead of perpendicular distance. It can be further analyzed by visualizing initial corresponding guess obtained for each ALS plane during processing.

- <u>Normal Angle Deviation between planes</u>:

Distance measurement is adopted to reduce search area for true correspondence in target dataset. After limitation made by distance measure, second measure adopted is normal angle deviation exist between planes of both datasets. Normal vector of a planar surface is depiction of planar surface direction and it has been calculated during RANSAC based plane-fitting. True correspondences are parallel to each other and parallel planes have same direction. However, proposed study is conducted in point cloud environment instead of solid surface planes therefore use of RANSAC to fit a plane always brings some minute difference in normal angle of parallel planes. True corresponding plane is almost parallel to plane for which correspondences are searched for. In other words, their normal vectors are almost in same direction and deviation (θ) between them can provide confidence about their correctness. If n_1 and n_2 are normal vectors of ALS and UAV planes respectively, then deviation between them is calculated as;

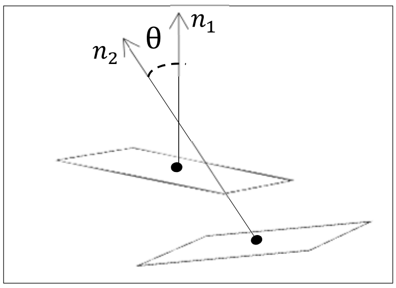


Figure 3.5(c): Normal angle deviation

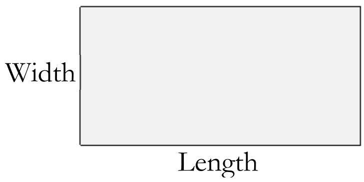
$$Cos\,\theta = \frac{n_1 . n_2}{|n_1||n_2|} \quad (3.5)$$

- <u>Segment size</u>:

Segment size is defined as total number of points that lies on a segment/surface. Size of segment is dependent on point density of a dataset. ALS and UAV dataset both have different point densities according to their acquisition methods therefore threshold value for both dataset will also be different. However, ALS dataset point density is known and is lower than UAV dataset. Segment size can be calculated approximately by simple calculation applied on planar surface only.

Area = Width × Length

Segment Size =Area × Point density/m²



Proposed study is about planar feature matching, therefore focus is to preserve only planar features in search space. Usually planar features/flat surfaces have more points as compared to linear, irregular shapes, etc. so therefore segment size value is considered important in reducing possible correspondences to only well-defined planar features in close neighborhood search space. An optimal and realistic value to preserve planar features is chosen for this purpose. This value must be selected critically especially for source dataset as number of planes for which correspondences are to be searched for are dependent on it. Large value of segment size may remove many good planes from dataset or may disturb well-distribution of planes in area. Removal of good planes can also minimize advantage of plane redundancy so optimality of threshold value is recommended for source dataset.

- Outlier Ratio:
  Outlier ratio found in a segment is also an important measure to limit algorithm only to well-defined planar features found for correspondence search in target dataset. A well-defined planar feature preserves its geometry and during plane-fitting process through RANSAC most of planar feature points become inliers. RANSAC algorithm is robust upto 50% of outlier existed within a segment but a good planar feature/flat surface does not contain much outlier during plane-fitting. A threshold value is set up for planar features and point lies outside this threshold value are considered as outliers. However, it is also pertinent to know that measurement errors are not the only reason for having outlier in a segment. Occluded planar features by some adjacent topographic features (trees, attached roofs, roofs having dormers, etc.) have also more outlier ratio although they are good planes. By putting threshold value for outlier ratio calculated for each segment, non-planar/segments having irregular shapes can be removed. Their removal from dataset enhances confidence for rest of segments to be planar.

Discussed measures are important for selection of only planar features for correspondence search in a determined neighborhood. Distance measure is important to specify close neighborhood range in a target dataset for source plane. Normal angle deviation is also important to consider only parallel planes found in already defined neighborhood. These two measures collectively provide important initial guess about correspondences. Correctness of this initial guess is discussed in next section. Other two measures segment size and outlier ratio are applied to have a confidence about planarity of initially selected planes. These are also helpful to confined to only planar surfaces. Small segments (non-planar) and noisy segments (irregular shapes) from search space will certainly be removed by applying these measures. Other additional measures include plane shape, plane area, etc. however these measures becomes ineffective due to similar geometrical pattern existence in close neighborhood and fail to improve correspondence search.

3.4.2. Correspondence Determination

After reduction of search space, second most important step is extraction of true correspondences found in target dataset for each source plan. In an urban scene, building structures exists adjacent to each other and it becomes more problematic as many building roofs have same geometrical designing or in simple words, many geometrical resemblances and symmetries do exist in close neighborhood. Due to this reason, even after adopting earlier discussed measures for space reduction, there is sure possibility for having wrong corresponding plane/segment in searching neighborhood. A robust, effective and reliable search plan is required to accommodate these problems. Proposed search plan must detect possible candidate correspondences in searching space neighborhood, reduce them to most possible candidates and evaluate them also to confirm their correctness. Algorithm works in two phases: in first phase (fig. 3.6) it provides initial guess about correspondences from target dataset based on distance and angle measurement and second phase is to evaluate them for their confirmation.

Measures discussed in previous section are good enough for provision of initial correspondences from target dataset. Possible candidates for correct correspondence can be more than one due to existence of symmetrical geometrical planar features in close search neighborhood. Evaluation of these initial correspondences is necessary to be used for final registration. Discussion about both cases (1:1 and 1: many) is described in following paragraphs;

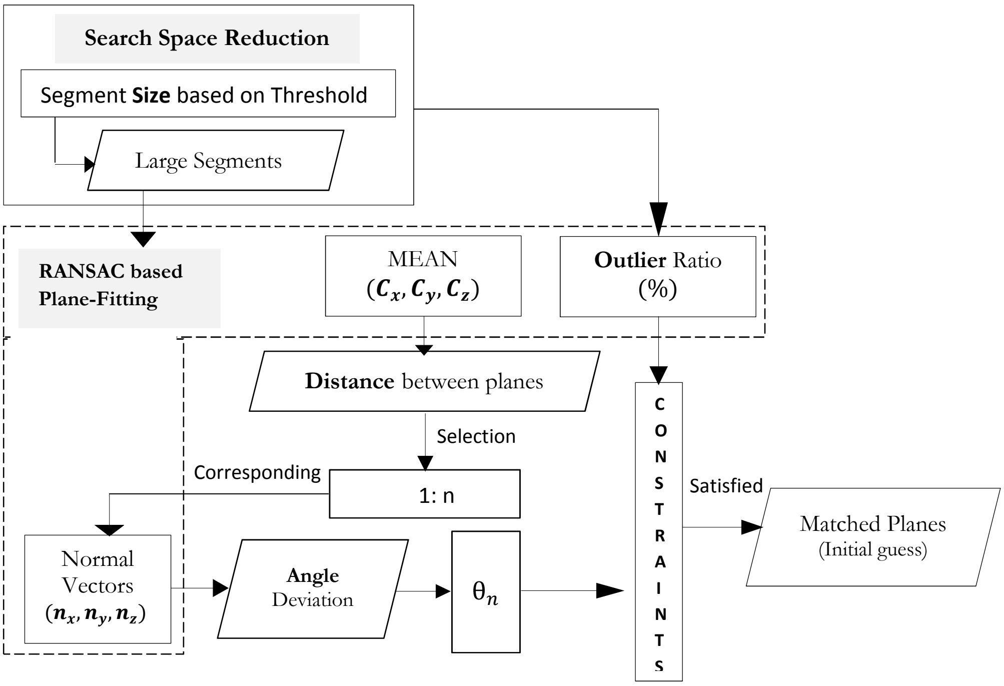


Figure 3.6: Feature Correspondence search plan (Phase I)

<u>1:1 correspondence</u>:
Both datasets are close enough each other therefore based on adopted measures, 1:1 correspondence can result in true correspondence. In an urban environment, many planes can exist in close neighborhood with same height, dimensions, shape, etc. therefore selection of correct correspondences becomes problematic (especially when all candidate correspondences are of same geometrical properties). Due to this occurrence, 1:1 selection can leads to wrong correspondence if selected on basis of earlier discussed measures. It is possible to have correct correspondence at a place other than first one therefore 1:1 approach can eliminate correct correspondence (fig. 3.7). This elimination lessens the advantage of redundancy of planar features to be used for reduction of registration errors.

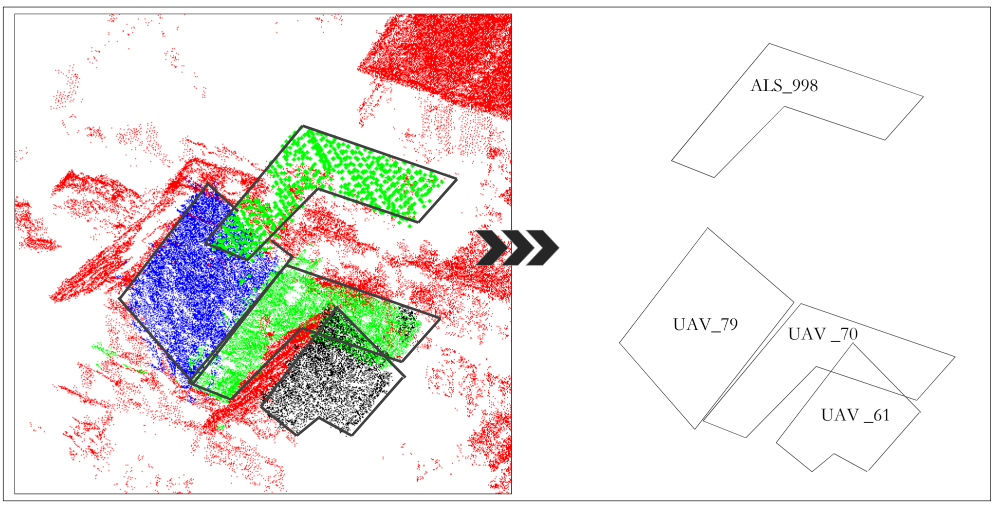


Figure 3.7: Wrong correspondence selection using 1:1 approach

Figure 3.7 is showing three possible candidate correspondences found in close search neighborhood area for single source plane. 1:1 approach is resulting in wrong correspondence at first place, so it will be discarded by putting threshold value for normal angle difference. In this case, source plane will have no

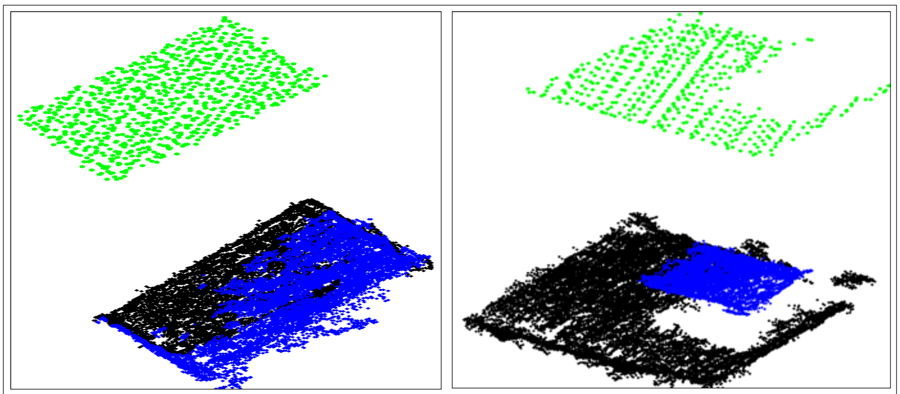
ALS Plane	Corr. UAV plane	Corr. Rank	Distance (<10 m)	Normal Angle Deviation (degree)	Segment Size (points/plane)	Outlier Ratio (%)	Status
998	79	1	8.25	51	13758	7.13	×
	70	2	8.42	2	11093	14.94	ok
	61	3	8.75	49	5669	3.68	×

Table 3.1: Numerical details of three corresponding planes from target dataset

correspondence but in reality it is there. Therefore application of 1:1 approach in urban environment seems in-appropriate to tackle these kinds of issues. Numerical details of candidate corresponding planes are shown in table 3.1. UAV plane no 79 is ranked as first on basis of distant measure and if 1:1 approach is applied than UAV plane no 79 will be discarded on basis of angle difference. Therefore ALS plane no 998 will receive any correspondence which is wrong. For said dis-advantage 1: many approach is adopted instead of 1:1.

<u>1: many correspondences</u>:
Disadvantages of 1:1 corresponding approach can be minimized by taking more than one plane as a possible candidate plane in search area. This 1: many approach consider all possible candidate planes found in close neighborhood search area and then reduction measures applied to them. This approach is robust with disadvantage we discussed in 1:1 approach. However, possibility of existence of wrong correspondence is still there due to symmetrical geometrical shapes in urban scene. Point dataset generated by exploiting UAV images, contains fragmented plane segments for one single surface plane. These fragmented planes are placed at different position of correspondence but in actual all of them are true correspondences of source plane. Advantage of 1: many corresponding approach will also take care of this problem. Disadvantage of 1: many approach is existence of parallel planes in neighborhood area which passes all reduction measures and remains there as a candidate correspondence of source plane.

In fragmented case (fig. 3.8(a)) both fragments belong to same planar surface and are correspondences of single source plane. 1: many approach will consider both of them and involve both of them in process of determination of transformation parameters. Roofs of buildings have multiple surfaces and during acquisition of data these multiple surfaces are considered as individual segments. These multiple surfaces (fig. 3.8(b)) are also parallel with source plane. These multiple/parallel surfaces are found within range of close search neighborhood and can pass adopted reduction measures. In 1: many approach, these surfaces appear as a possible correspondence candidate for source plane although they are wrong. Fragmented planes are true candidates also but it increase computational cost of algorithm because number of pairs will be increased. Evaluation of these correspondences is discussed in next section.



(a) Fragmented planar surfaces (b) Multiple (parallel) surfaces

Figure 3.8: Selection of fragmented and multiple planar surfaces using 1: n approach

3.4.3. Evaluation of initial correspondences

Initial correspondences obtained by adopting earlier discussed measures and 1: many approach still cannot be considered as true correspondence. Evaluation of these correspondences is needed to be carried out for confirmation about their correctness. These initial correspondences can be evaluated by analysing residuals of distances between ALS and UAV dataset (after rigid transformation). Extraction of matched planes between source and transformed UAV dataset is confirmation of correctness of correspondences achieved in phase I. Diagram of phase II is shown in figure 3.9 and detailed description is given in following paragraphs step by step.

i) Evaluation of initial correspondences start from selection of planes from initially extracted matched planes. After adopting search space reduction measures, 'n' number of matching pairs are obtained. For computation of parameters, minimum three matching planes are required to estimate the homography that exists between them. Selection of more than three planes from initial matched planes can make algorithm expensive in time as number of combinations are increased. Combinations of three selected pairs can be achieved by following mathematical formula;

$$nCr = \frac{n!}{r!(n-r)!} \tag{3.5}$$

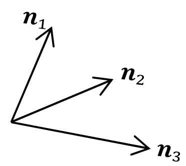
n = number of corresponding pairs
r = minimum selected pairs
For a single source plane, many possible candidates from target dataset might claim to be true correspondence of it. Therefore from matched pairs instead of source plane, planes from target dataset are selected for combination formation. Number of combinations is directly proportional to total number of matched pairs obtained after initial matching (Eq. 3.5). In other words combinations frequency is indirectly dependent on threshold value adopted for segment size of source dataset. Each combination/triplet is to be exploited in rigid transformation for computation of residuals (standard deviation & mean) of distances between source plane and target plane points.

ii) After forming a combination, its geometrical alignment is assessed. Mathematically, three planar surfaces are declared orthogonal when scalar triple product of their normal vectors is non zero. In other words, their point of coincidence is same or they intersect at single point. This orthogonality condition (a good check at non-parallelness of selected three planes) is mathematically described as;

$$\mathrm{n}_1 \,.\, (\mathrm{n}_2 \times \mathrm{n}_3) \neq 0 \tag{3.6}$$

Or,

$$\begin{vmatrix} n_{1x} & n_{1y} & n_{1z} \\ n_{2x} & n_{2y} & n_{2z} \\ n_{3x} & n_{3y} & n_{3z} \end{vmatrix} \neq \mathbf{0}$$



Terms n_1, n_2 and n_3 are normal vectors of three planes. This value should be significantly non-zero and it would be better to set a threshold value for determinant value to keep only reliable non-parallel combinations. It will automatically discard those weak combinations whose determinant

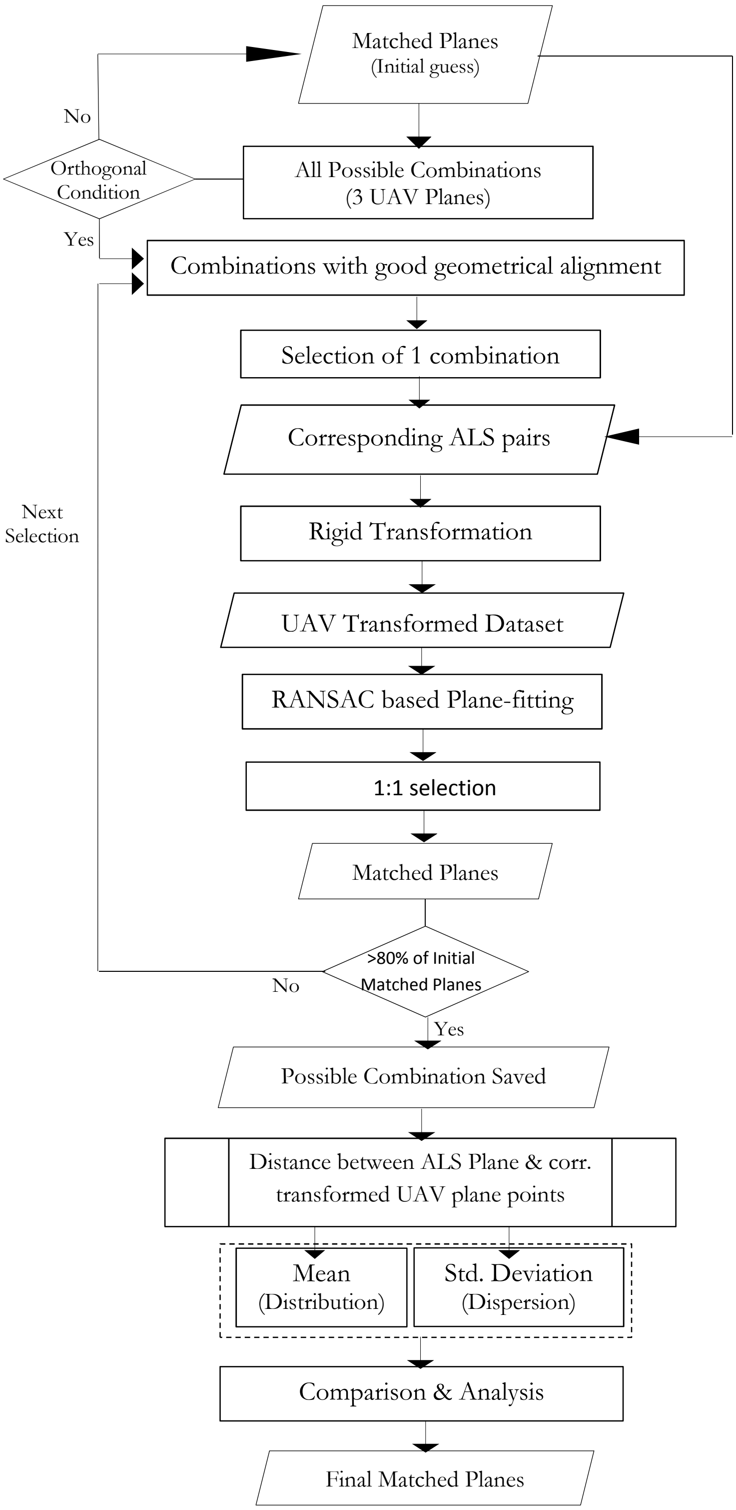


Figure 3.10: Feature Correspondence search plan (Phase II)

values will be near to zero. This condition cannot be imposed if four planes are selected as discussed earlier and algorithm has to consider all those combinations which have weak geometry also.

iii) After selection of three planes (one combination) from matched pairs, their corresponding matches are attached with them to form pairs. Plane information about these matched pairs is already obtained during plane-fitting process and this information is exploited as input for computation of transformation parameters.

iv) For evaluation purpose, rigid transformation is executed between both datasets to analyze correctness of obtained initial correspondences. For rigid transformation, plane-to-plane approach is applied. If initial correspondences are correct in triplet then approximately correct transformation parameters (R & T) are achieved. These achieved R and T are applied to UAV dataset to transform it towards ALS dataset. After transformation of target dataset, RANSAC based plane fitting is applied to extract plane parameters of transformed dataset. Euclidean distance is computed between ALS and newly transformed UAV dataset for determination of matched planes again between these datasets.

v) In phase I, 1: many approach is applied but after transformation only 1:1 approach is applied because if R & T are computed correctly than true correspondence will occur at first place. If this first place matched plane is same as achieved during phase I, than this is confirmed as true correspondence.

vi) After correct transformation almost all planes moves toward source dataset and combinations for which more than 80% planes are retrieved as confirmed planes are saved. This threshold value of 80% is dependent on constraint values of distance and angle difference introduced second time. Strict constraint value can give no correspondence and soft value can result again in wrong correspondence.

vii) Distance between each source plane and its corresponding points of target plane are calculated for combinations passing above condition. Mean and standard deviation of these distances are also computed after transformation for these combinations. These measures are considered as residuals achieved after rigid transformation (Bae & Lichti, 2008). Analysis of both measures is performed and planes involved in best combinations are then further used for final registration.

3.5. Registration Process

Analysis of mean and standard deviation, results in true corresponding planes fit for final registration process. Registration can be achieved by exploiting only three corresponding plane pairs however redundancy of planes is recommended to minimize random errors. Exploitation of more than three correspondences enables algorithm to perform least square adjustment. Selection of more than three corresponding planes is made by selecting more than one combination having low mean and standard deviation values (low residuals). Redundancy of available correct correspondences is helpful in determination of optimal transformation parameters by reducing registration errors with the help of least square adjustment method.

Registration process starts after finding true correspondences from target dataset. True correspondences are determined after analysis of residuals (mean & std. deviation) and are exploited for registration purposes by adopting certain feature matching approaches. For aimed study, plane-to-plane and point-to-plane approaches are performed and analysed based on accuracy achieved after final registration.

3.6. Conclusion

This chapter describes developed technique for extraction of features from point cloud, determining true correspondences from target dataset for their exploitation in computation of transformation parameters to register both datasets. Previously developed algorithms are incorporated in devised method for feature extraction and a correspondence search plan is developed based on four measures for automatic detection of correspondences from target dataset. Evaluation of these obtained correspondences is carried out by statistical measures about their correctness.

Pre-analysis and pre-processing are considered as two important steps for data preparation for registration purpose. Surface growing technique is adopted for datasets to extract feature information from them. Plane-fitting for each segment is than performed by exploiting well-renowned algorithm RANSAC, considering its robustness to handle large amount of outliers found in datasets. PCA is performed for computation of plane parameters during this step. Information extracted during plane-fitting process is utilized for determining initial correspondences found from target dataset. Pre-hand knowledge about datasets is important for setting up different threshold values for correspondence search. These initially obtained correspondences are than evaluated with the help of residuals (mean & std. deviation) obtained after rigid transformation. As final step these evaluated correspondences are than used as input for final registration.

In an urban environment, to avoid wrong correspondences obtained due to existence of symmetrical shapes in close search neighborhood, 1: many searching approach is presented instead of 1:1. By adopting above all described measures, presented method is robust enough to extract planar features, detect their initial correspondences from target dataset, evaluate them and register both datasets by exploiting different matching strategies.

4. IMPLEMENTATION AND RESULTS

Implementation of algorithm developed in last chapter and results achieved through this are included in this chapter. Section 4.1 provides general overview of datasets used for implementation of algorithm. Pre-analysis and pre-processing of these datasets are described in section 4.2. Results of RANSAC based plane-fitting/feature extraction are discussed in section 4.3., which is then followed by implementation of correspondence search plan in section 4.4. Impact of adoptive search space reduction measures, correspondence determination and their evaluation are also included in this section. LAStools and Point Cloud Mapper (PCM) are also used for data pre-analysis and pre-processing. Matlab (version 8.1.0.604, R2013b) is used for pre-analysis, algorithm development.

4.1. Datasets

Both datasets used for this study are point cloud datasets with different characteristics. Comparison of both dataset to have a general overview in tabular form is depicted in table 4.1.

	ALS	UAV
Point density	10 points/m²	In-Consistent density
Coordinate System	Amersfoort / RD New	Amersfoort / RD New
Acquired by	Standard ALS procedure	Micro Drone
Acquisition time	2007	2012
Acquisition method	Airborne laser scanning	Dense image matching
No. of Points	77365	5281949
Covered Area	0.04 sq. Km	0.04 sq. Km
Coverage Area	Nunspeet, The Netherlands.	Nunspeet, The Netherlands.

Table 4.1: Comparison of ALS and UAV datasets

ALS Dataset

ALS dataset used for this research is subset of national dataset AHN-2, which is second part of the Actueel Hoogtebestand Nederland (AHN) project. This project was initiated for acquisition of high-resolution altimetry data over entire Netherlands using airborne laser scanning (Sande et al., 2010). ALS used in this research study was captured over city of Nunspeet, the Netherlands in 2007 (fig. 4.1).

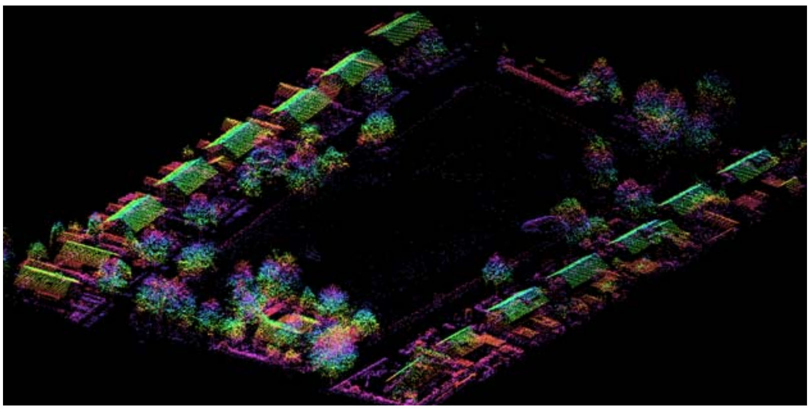


Figure 4.1: Visualization of ALS dataset using PCM over Nunspeet, Netherlands. (2007)

UAV Dataset

UAV dataset was acquired by Dutch Kadaster in June 2012. They used a micro drone named as MD4 - 1000, equipped with a camera model Olympus E-P3 OGT with a focal length of 17mm. A total of 380 images with 80% overlap at flying height of 60m were captured. Image size obtained was 4032 x 3024 pixels with pixel size of 4.4 µm. Resolution of UAV images (ground sampling) has been computed by exploiting this information;

$$\text{Ground Sampling Distance (GSD)} = \frac{\text{Pixel size} \times \text{flying height}}{\text{Focal length}} \tag{4.1}$$

$$= \frac{4.4\ \mu\text{m} \times 60\text{m}}{17\text{mm}}$$

$$= 0.0155\ \text{m or } 1.55\ \text{cm}$$

Computed value of GSD for UAV images is a proof that images are of very high resolution. This high resolution (not only) affects point density of point cloud data generated through images and makes it denser. Detailed process about point cloud generation has already been discussed in chapter 2 under section 2.2. 3D point cloud generated by dense image matching technique is shown in figure 4.2 using point cloud mapper software.

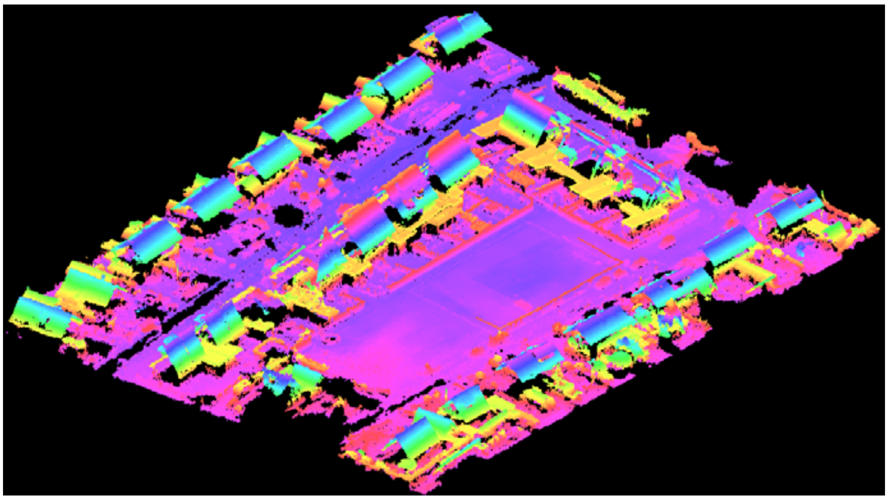


Figure 4.2: Generated Point Cloud through UAV images and visualized in PCM

4.2. Data Preparation

This section consists of three parts. Analysis of both datasets, filtering outputs and segmentation outcomes will be discussed in first, second and third subsection, respectively.

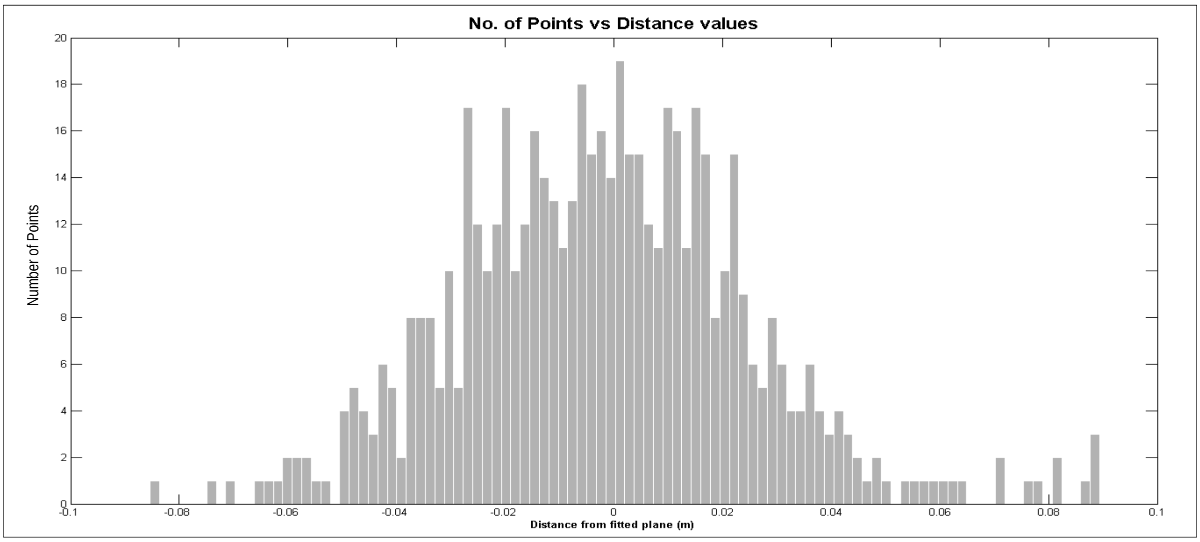
4.2.1. Data Analysis

Data analysis of both datasets gives us useful information about datasets. Proposed study is only about planar features therefore evaluation of planar features (only roof planes) accuracy provides us valuable information about their compactness/density. Analysis of planar feature provides information e.g. point density per plane, threshold value to fit a plane, accuracy of a planar feature (noise), etc. Achieved values are noted down and further used for surface growing and plane-fitting process to achieve reliable results.

	ALS planar features					UAV planar features				
	1	2	3	4	5	1	2	3	4	5
Total no. of points	1072	1006	1054	751	1366	23566	23202	28058	11093	34781
95 % (2σ)	1018	958	1001	713	1297	22388	22042	26655	10538	33042
Distance threshold	0.08	0.06	0.08	0.08	0.07	0.20	0.20	0.25	0.40	0.20
No. of outliers	27	29	53	17	63	513	710	1039	375	1628
Dist. Threshold (avg)	0.07m					0.25m				

Table 4.2: Details of five selected planar features of both dataset

To take a broader view of both datasets, five planes from each dataset are analysed. Selection of points, lies on a single plane is made carefully to make our results more realistic and reliable. Selected planes are randomly selected and having good geometrical dimensions. RANSAC algorithm is exploited to fit a plane within each selected planar feature. Table 4.2 is showing details of five selected planar feature in both datasets and adopted value of distance threshold for fitting a plane. This value of distance (between point & fitted plane) is selected in such a way that 95% points of selected planar feature become inliers. Distances of points (inliers) from fitted plane are normally distributed at this value. This value of distance form fitted plane is directly proportional to noise present in dataset and therefore is different for both datasets.



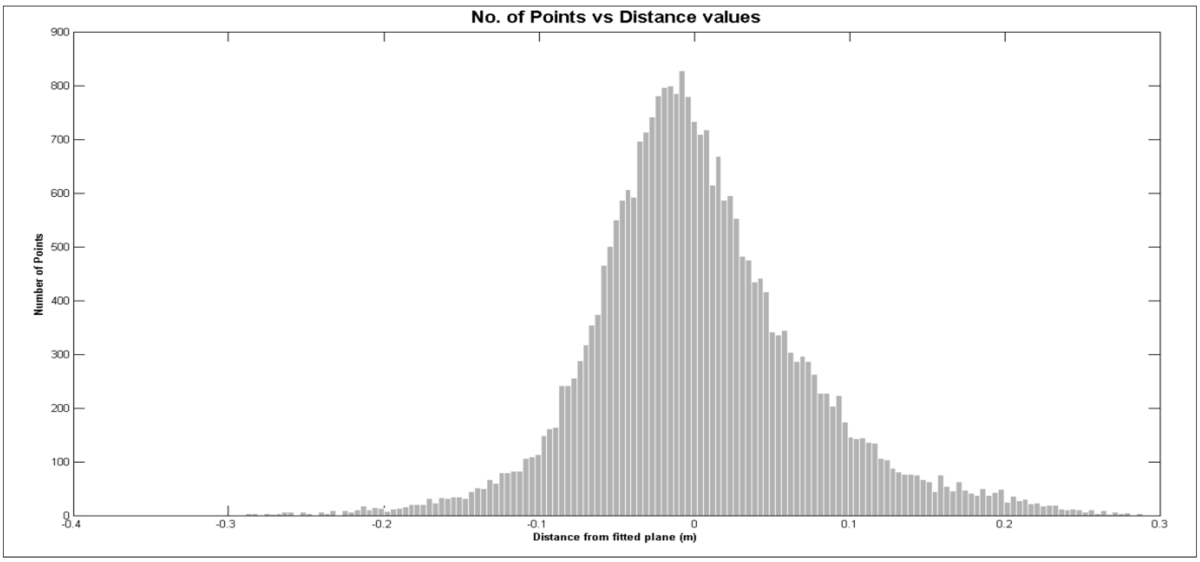


Figure 4.3: Comparison of Planar accuracy with signed distance values (above) ALS (below) UAV

Computed distances with fitted plane are plotted against number of plane points and are shown by histogram bar chart, describing their attitude within both datasets. In reality, distance can never be negative but theoretically it occurs when observations are accumulated around zero on both sides. These are called signed values of distances. Figure 4.3 is depiction of computed distance values of inlier points from fitted plane. Plane is fitted in flatted surface through RANSAC algorithm and statistical 2σ rule is exploited for selection of points as inliers. Planar features selected from both datasets results in quite normal distributions.

For ALS dataset (fig. 4.3(above)), selected feature has mean of 0 and standard deviation of 0.06 m which means that points are evenly distributed for ALS planar surface and has dispersion of 6 cm around fitted plane. In other words, observations (distance values) are concentrated at an equal distance of 6 cm from fitted plane surface. For UAV dataset (fig. 4.3(below)), signed values of distances also results in normal distribution but with standard deviation of 25 cm value. It has mean of 0 and standard deviation of 0.25 m which means that inliers point are evenly distributed at distance of 25 cm above and beneath fitted plane surface. Standard deviation (dispersion) value of UAV dataset is 0.25 m which is quite large as compared to ALS dataset. Analysis of planar features accuracy of both dataset in signed values provides us useful information about their dispersion for planar surfaces. . In ALS and UAV dataset dispersion of points is around 6 cm and 25 cm, respectively. Selected features are planar features therefore values are valid for planar features. These values are helpful during plane fitting process to consider 95% of points of planar surface as inliers. For ALS dataset, number of points (point density) on y-axis of histogram is much less than UAV dataset proving ALS as low density dataset.

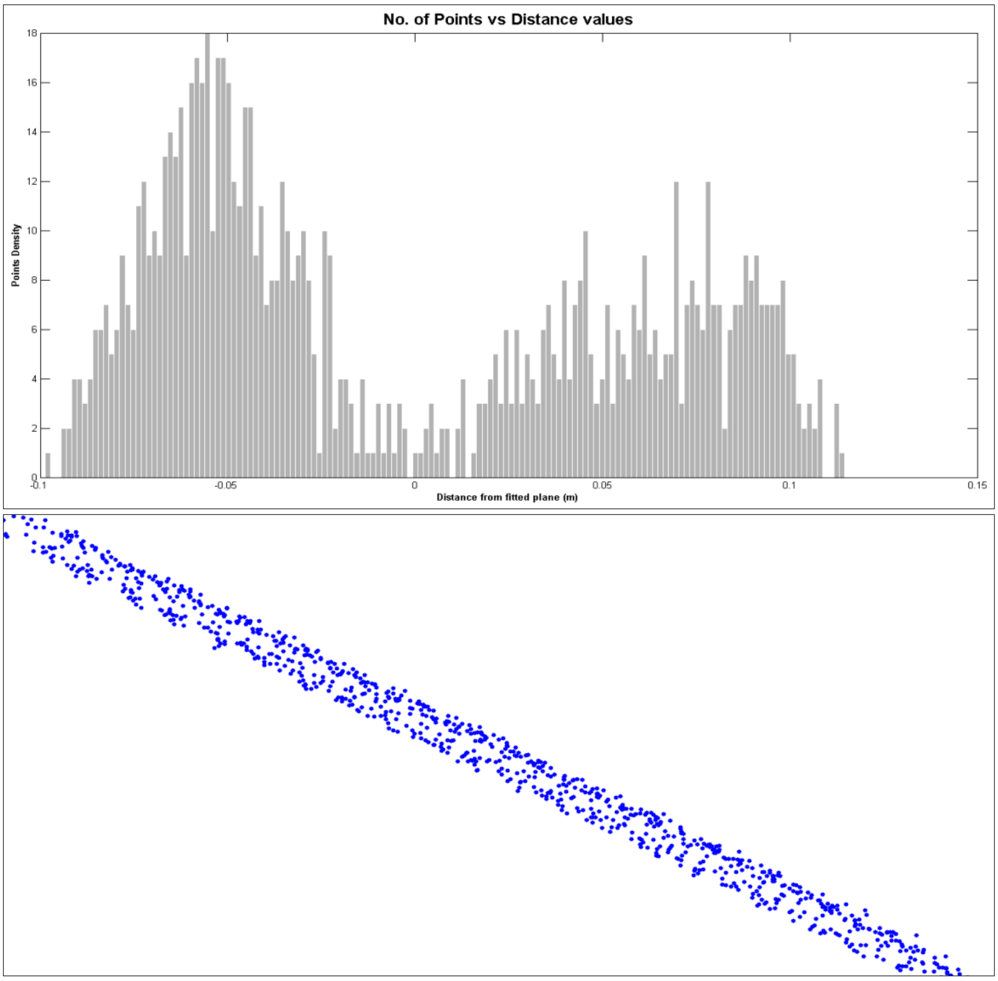


Figure 4.4: (a) bimodal distribution (b) ALS plane with two surfaces

Beside this information, some other information is also extracted from this analysis. An ALS plane is resulted in bimodal normal distribution by adopting same parameters. One of such bimodal distribution is presented by histogram bar chart in figure 4.4(a) and ALS plane having double surfaces is also shown in figure 4.4(b). In this case, number of points on ALS plane are increased and Standard deviation value almost becomes double than a normal ALS plane. (Standard deviation value is 11 cm instead of 6 cm). This bimodal distribution of ALS plane points and multi-surface visualization is an indication that plane might lies within overlapping regions during laser scanning.

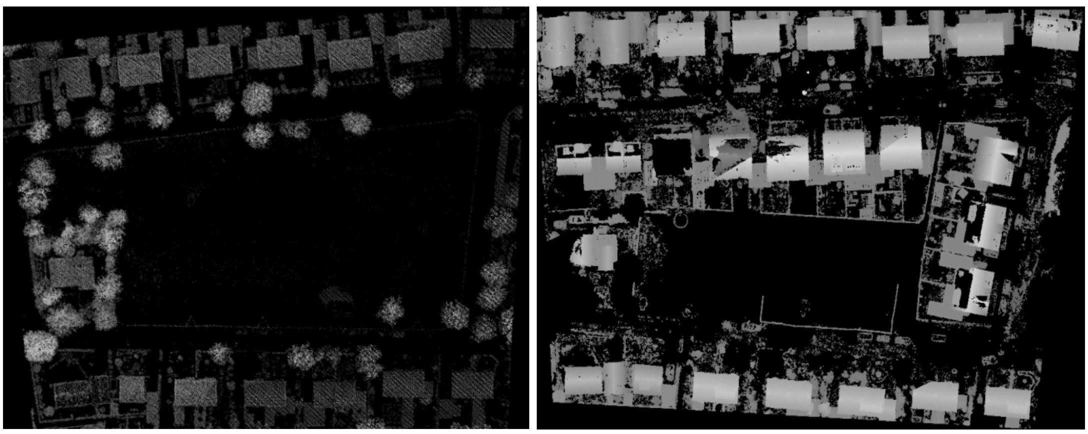
	Mean	Std. Dev
ALS plane	0	0.0601
UAV plane	0	0.2525

Table 4.3: Outcomes of Planarity Accuracy for both datasets

To conclude this discussion, information given in table 4.3 is an outcome for planar feature accuracy of both datasets. Mean values of these planar surfaces are zero which is an indication that planes are really planar/flat surfaces and computed values of distances are evenly distributed above and beneath fitted planar surface. However dispersion (standard deviation) of points (inliers) for both datasets is different depending on their accuracy. ALS having lower standard deviation value than UAV dataset is depicting accuracy of ALS dataset. This low value of standard deviation shows compactness of ALS dataset which needs only 6 cm to accommodate 95% of points for its planar surface to fit a plane. Non-planar feature will not fit a plane at these values with normal distribution. This standard deviation value is used in further processing i.e. surface growing, plane estimation, etc. Point density along y-axis of histograms depicts density of both datasets. Pre-processing of datasets is next step of data preparation and is discussed in next section.

4.2.2. Filtering

LAStools software's component 'lasground' (Axelsson, 1999) has been used to filter UAV data by adopting appropriate parameters. M. Gerke and Xiao (2014), have also used it for classification of Lidar data into ground and off-ground data. Scene under discussion is of city area of Nunspeet, the Netherlands therefore selected parameter for terrain nature is city. Second important parameter is threshold value to decide which point has to be classified as ground or off-ground point. Although roof planes/buildings are considerably high above ground but to keep all planar features above ground, value of 0.5 m has been selected. By selecting this value, successfully removed ground points from scene and almost left with only points above ground (Fig. 4.5).

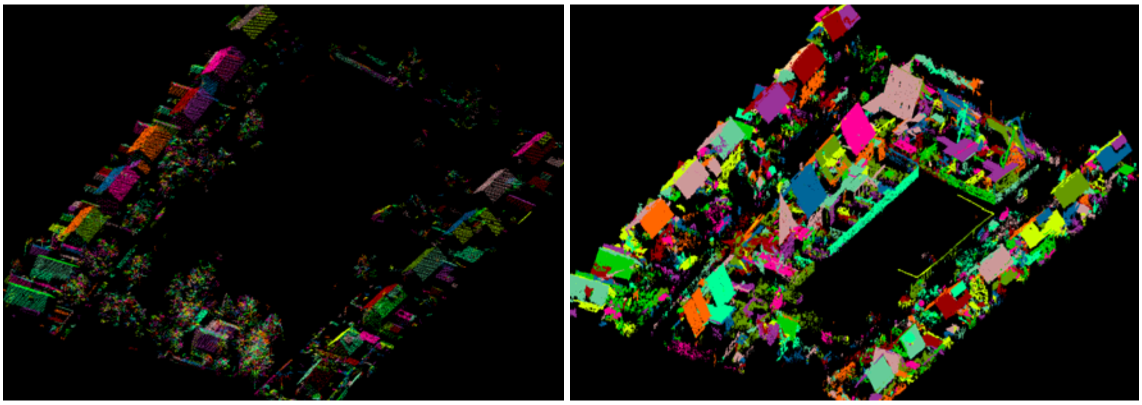


(a) ALS Dataset (b) UAV Dataset

Figure 4.5: Outcome of LAStools applied on both datasets

4.2.3. Surface Growing/Segmentation

Surface growing takes place after filtering of datasets and region growing algorithm developed by Vosselman. et al. (2004) is exploited using PCM software. Interested features for proposed study are planar features (roof planes) therefore suitable surface growing parameters have been adopted. In seed detection step, value for seed neighborhood radius has been selected 1.0 m for both datasets. For surface growing parameters, values obtained during planarity accuracy are helpful for surface growing phase. These values are manoeuvred in such a way that mostly planar features are preserved in both datasets. Surface growing radius for both datasets is kept as 1m but maximum distance to surface is set as 0.10 m and 1.0 m for ALS and UAV dataset, respectively. Minimum distance required for re-computation of local plane is set as 0.10m and 0.30m (near to initial values gained in planar accuracy measurements) for ALS and UAV datasets respectively. Outcome of surface growing algorithm is presented in figure 4.6 and segmented datasets with segment ID's are used directly as input for further process.



(b) ALS dataset (a) UAV dataset

Figure 4.6: Outcome of Surface growing applied on both datasets

4.3. RANSAC based Plane Fitting

RANSAC algorithm is exploited for fitting planar features in both datasets and plane parameters are computed for each segment after surface growing process. RANSAC is robust to deal with noisy datasets (UAV dataset) however, as discussed in Chapter 3, section 3.3.1, plane parameter '**d**' (perpendicular distance from origin) is sensitive and it generate results with quite large differences at each run (Table 4.4). This abrupt and huge change in plane parameters brings numerical instability during computation of transformation parameters (especially in translation factor). To overcome this problem, normalization of datasets is executed and shift is introduced in both datasets to bring them near origin. By doing this, difference in plane parameter (**d**) almost becomes stable (Table 4.4) with RANSAC. More abrupt changes can be seen for UAV dataset as compared to ALS dataset before normalization.

	Distance from origin (before normalization)		Distance from origin (after normalization)	
	UAV	ALS	UAV	ALS
Plane No.	**2**	**33**	**2**	**33**
1st run	70220.36	112662.9	16.7564	35.0607
2nd run	78252.62	112774.6	16.7457	35.1197
Difference (m)	1967.74	111.7	0.0107	0.0590

Table 4.4: Effect of RANSAC on plane parameter'**d**'

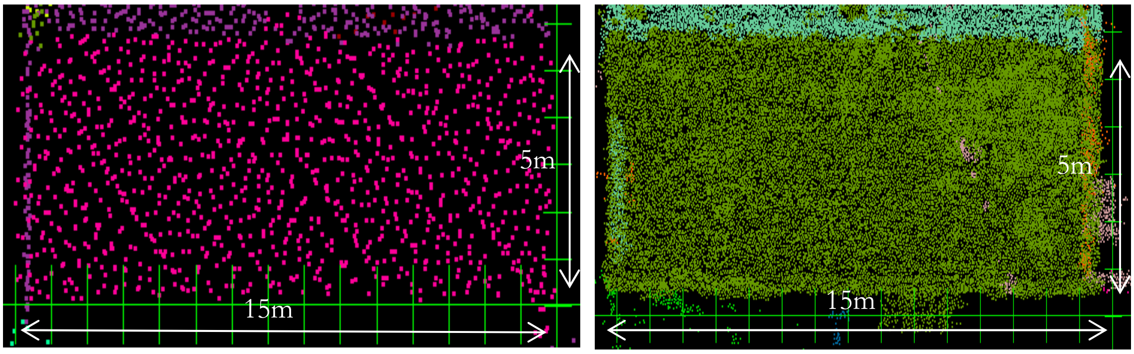
4.4. Feature Correspondence Search Plan

4.4.1. Search space reduction

Segment Size:

Segment size (number of points on a segment/roof plane) is considered as first constraint to reduce search space. Focus of study is plane based matching therefore interesting features are roof planes and an estimate about point density of these features is important for their preservation. A gable roof plane of same building along with its length and width exist in both datasets is depicted in figure 4.8. Point density of ALS dataset is 10 points/m², therefore points on such planar roof are estimated as;

$$\text{Segment Size of ALS (approx.)} = 75 \times 10 = 750 \text{ points/segment}$$



(a) ALS gable roof (b) UAV gable roof

Figure 4.8: Segmented gable roof planes of same building

This estimation provides an initial guess about threshold value selected for preservation of these planar features. To preserve more and more planar features in dataset for exploitation of redundancy, adopted value for ALS dataset should be less than computed value. For UAV dataset, due to inconsistent point density of data, such kind of threshold cannot be computed however selecting few very good planes manually from UAV dataset and averaging their point density is reasonable approach for selection of threshold value. Manually selected five UAV planes and their point densities are presented in table 4.5 (a).

	UAV Full Planes			UAV fragmented planes		
Plane ID	2	349	1098	815	830	578
Segment Size	23566	28058	26895	7718	6861	4421
Average value (points/plane)		26173			6333	

Table 4.5: Segment size for UAV full and fragmented planes case

Table 4.5 depicts point density for planar features (full & fragmented planes). These values provides us information about both type of planar features found in UAV dataset. However adopted value is selected 4000 points/plane to preserve more and more planar features in target dataset. Threshold value is crucial for ALS dataset because of its low point density. It affects number of ALS (source) planes for whom correspondences have to be determined. Selection of large (tight) threshold can also affect their well-distribution in scene by removing planes from there. Large value of segment size reduce advantage of redundancy and can hamper well distributions of planes in scene while lower value can make algorithm computationally expensive and possibility of getting non-planar surface increases. For UAV dataset, point density is much higher than the ALS dataset therefore segment size has no real effect on plane frequency however above mentioned value is adopted for removal of minor features.

Outlier Ratio:

Another important measure adopted is to filter out possible candidate target planes by looking at outlier ratio they have. RANSAC method is applied to each segment in plane-fitting process and some points of each segment are detected as outliers. Outlier ratio can be a good measure to describe a segment as a flat surface. However connected planar segments can also have higher outlier ratio but discuss study is only about smooth and flat surfaces. Large outlier ratio increases possibility of that feature to be non-planar. To limit correspondence search, it is another good idea to already delete those segments which are non-planar or which have large ratio of outliers.

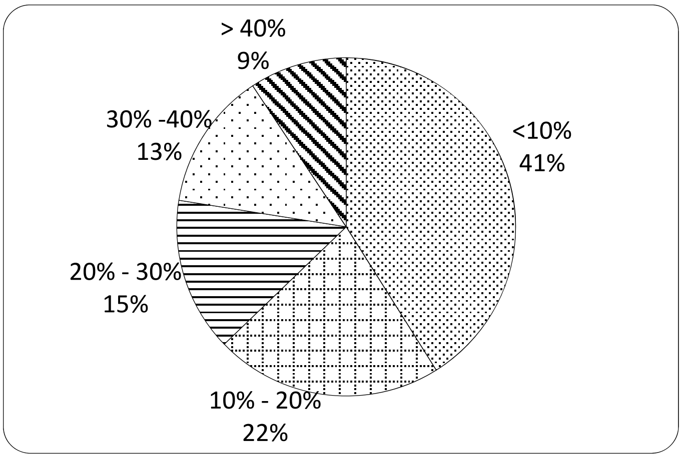
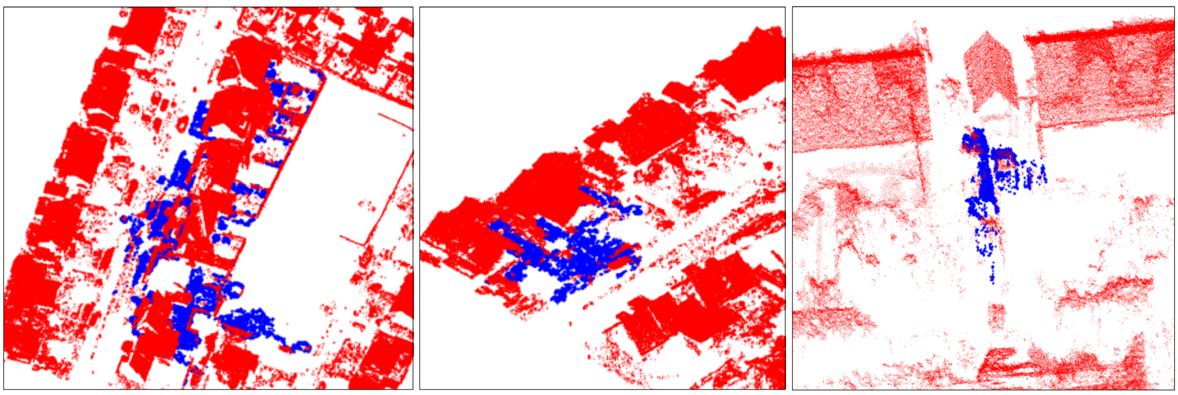


Figure 4.9: Outlier ratio proportion found in UAV dataset

A pie-chart depicting proportion of outlier ratio percentage for UAV segments is shown in figure 4.9. Almost half of segments of UAV have less than 10% outlier ratio and since planar features has lower outlier ratio therefore possibility of UAV planar features increases for their existence in lower ratio proportion. To put threshold value for removal of non-planar surfaces from target dataset, pie chart (fig. 4.9) draws an impression about proportion of segments containing amount of outliers. Instead of putting 10% as threshold value, 20 % is selected which means 63% of segments are saved for further process and 37% are discarded or declared as non-planar by this measure (fig. 4.9). Three prominent segments having outlier ratio more than 20% can be seen in figure 4.10. These types of features which are useless for feature based matching should be removed from close neighborhood to limit search space for source plane.



(a) UAV segment 41 (41%) (b) UAV segment 105 (42.5%) (c) UAV segment 362 (25%)

Figure 4.10: UAV Segments along with Outlier ratio

4.4.2. Feature Correspondences

To find out feature correspondences, 1: many approach is adopted instead of 1:1 approach. Advantages and disadvantages of both these approaches are already discussed in chapter 3 under section 3.4.2. Adopted number of possible candidate correspondence is 5. For each source ALS plane, 5 possible UAV candidate planes come up to prove its correctness with source plane. Table 4.7 is showing 5 possible UAV correspondences initially extracted from UAV dataset based upto fifth minimum distance from source ALS plane.

Sr. No	ALS Plane (ID no.)	5 Possible Candidate UAV Planes (ID no.)				
		1st	2nd	3rd	4th	5th
1	**7**	1098	1	5	2	238
2	**15**	2	1098	237	1	5
3	**33**	200	222	207	203	194
4	**45**	203	200	222	207	194
5	**70**	188	192	333	198	243
6	**81**	198	188	243	242	192
7	**159**	352	356	359	349	355
8	**183**	349	352	356	359	355
9	**301**	371	951	377	381	367
10	**333**	951	371	381	377	367
11	**407**	670	692	665	688	686
12	**442**	665	643	670	692	688
13	**504**	652	654	659	661	663
14	**517**	659	661	652	663	654
15	**998**	70	61	143	73	79
16	**1157**	79	82	146	70	73
17	**1258**	1028	533	1049	1050	533
18	**1409**	533	1028	1049	532	1050
19	**1458**	830	815	833	824	785
20	**1479**	826	824	830	833	815
21	**1819**	1019	1018	1066	1017	1014
22	**1870**	579	578	541	576	580
23	**1885**	541	579	580	578	542

Table 4.7: Five possible candidate UAV planes for one ALS plane

Distance & Normal Angle Deviation:

After selection of five possible correspondences from target dataset (table 4.7), pre-hand knowledge of distance exist between both datasets. Both datasets are coarsely aligned to each other and are approximately 8 meter away from each other (fig. 1.2). To select true correspondence from these 5 possible matches, threshold value selected for distance measure is 10 meter. Second important measure adopted jointly with distance threshold is to select threshold value to allow difference occur between ALS plane and five corresponding UAV planes. True correspondences have same normal vector because both datasets have not much distortion in rotation (fig 1.2). However, in point cloud environment where surfaces are not solid and RANSAC algorithm is applied to fit plane deviation always occurs in normal vector direction. Dold and Brenner (2006), have set this value 1^{o} for finding correct correspondences. A very simple and basic calculation is performed to take initial guess about selection of threshold value for allowable angle difference between normal vectors of planes.

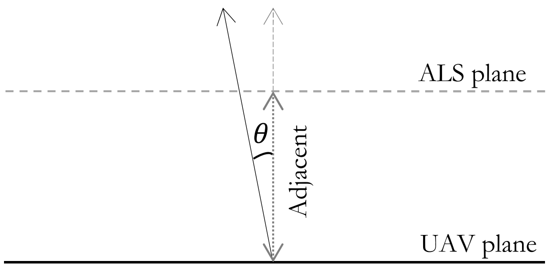


Figure 4.11: Estimation of threshold value for normal angle deviation

Calculation is based on some assumptions and exploiting simple trigonometric tangent rule;

$$tan\theta = opposite/adjacent \quad \text{Or} \quad \theta = tan^{-1}(opposite/adjacent) \tag{4.2}$$

Both datasets are geo-referenced and pre-hand knowledge about datasets, provides information about difference found in z-coordinates and difference computed is almost 9.28 meters. This difference is shown as adjacent in figure 4.11. Assumed allowable deflection (opposite) in planes is considered as 1 meter. Submitting these assumed/computed values in above formula results as;

$\theta = 6.15^0$

If assumed deflection is 2m,

$\theta = 12.16^0$

Putting large value for normal angle deflection can result in many wrong correspondences for each source plane and make algorithm expensive, therefor value obtained for 1 meter deflection is selected as threshold value for normal angle allowed deviation. Any corresponding UAV plane having angle deflection greater than this value is discarded from list. Reducing search space and applying these measures, outcome for initial guesses against each source ALS plane is shown in table 4.8.

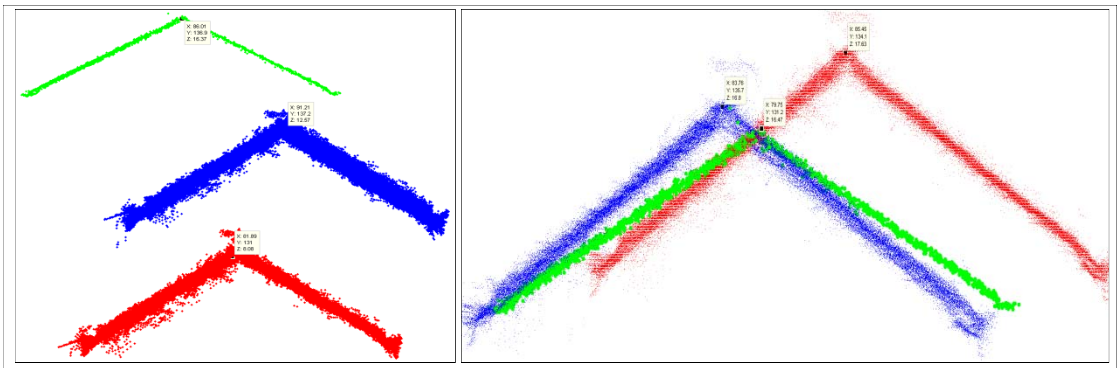
Sr. #	ALS Plane (ID no.)	Corresponding UAV Planes (ID no.)			Sr. #	ALS Plane (ID no.)	Initial Corresponding UAV Planes (ID no.)		
		1st	2nd	3rd			1st	2nd	3rd
1	**7**	1098	-	-	13	**504**	652	-	-
2	**15**	2	-	-	14	**517**	659	-	-
3	**33**	200	-	-	15	**998**	70	-	-
4	**45**	203	-	-	-	**1157**	-	-	-
5	**70**	188	-	-	-	**1258**	-	-	-
6	**81**	198	-	-	16	**1409**	533	-	1049
7	**159**	352	-	-	17	**1458**	830	-	-
8	**183**	349	-	-	18	**1479**	826	-	-
9	**301**	371	-	-	19	**1819**	1019	-	-
10	**333**	951	-	-	20	**1870**	578	579	-
11	**407**	670	-	-	21	**1885**	541	-	-
12	**442**	665	-	-					

Table 4.8: Initial correspondences found with their positions

Most of correspondences appeared at 1st position but some exist also at other than first position. For two source planes (highlighted in table 4.8), there appears no correspondence from target dataset and for two source planes, there comes more than one correspondence. No correspondence means either source planes are situated in corner of scene and because of shift their true correspondence is missing in target dataset or they have no correspondence due to structural change (temporal shift effect). Another reason for no correspondence is effect of RANSAC algorithm on adopted threshold value for angle difference deviation. Therefore corresponding plane pair which has normal angle difference near to applied threshold value may come at one run and may not come at next run. More than one correspondence may contain right and wrong correspondences/parallel planes because of multiple surfaces effect (fig. 3.8(b)) or may have fragmented parts of one target plane for each source ALS plane (fig. 3.8(a)). Correspondences appeared only on basis of angle and distance measures are not considered as true correspondences and are evaluated further. Evaluation process is discussed briefly in chapter 3, section 3.4.3.

4.4.3. Correspondence Evaluation

Evaluation of these correspondences for their confirmation is executed by developed algorithm (fig. 3.10) discussed in previous chapter. By putting threshold for geometrical alignment of planes, all combinations with true correspondences generate good results. Few combinations which are non-parallel but concentrated only in specific area/corner area of scene may have large residuals. During processing it is observed that non-rigid transformation has been used for evaluation of initial correspondences (Table 4.8) and it brings UAV data within 3-4 meter range after correct correspondences even. This is not acceptable and it doesn't fulfil purpose of algorithm. This phenomenon is also discussed by Tubic et al. (2003) that registration strategies are sensitive with large distance between them. Expensiveness of point-to-plane approach/non-rigid transformation has forced to exploit plane-to-plane rigid transformation for evaluation of initial correspondences. Figure 4.12 is depicting effect of vertical shift application on target dataset. Applying plane-to-plane (rigid transformation) approach with true correspondences provides distance residuals not less than 3 meter (fig. 4.12(a)) while after applying vertical shift, residual lies in 1m range (fig. 4.12(b)). Its numerical details are also sketched in graphs shown in fig. 4.13. Application of vertical shift also enhances determination of true correspondences between both datasets.



(a) Before vertical Shift application (b) After vertical Shift application

ALS dataset UAV transformed dataset UAV original position

Figure 4.12: Effect of vertical shift applied on UAV dataset

After computing distance between source plane and corresponding target plane points, residuals (mean & standard deviation) are analysed. Combinations having true correspondences resulted in low residuals after rigid transformation. After transformation only 1:1 search is applied subject of constraints which resulted in 18 planes as true out of 23 initial planes. There are three reasons for which these 5 planes are removed. Removed planes may not be correct one or they might be located in corners of scene or they may not prove themselves correct at first position after rigid transformation. Distribution of these planes can be seen in figure 4.14.

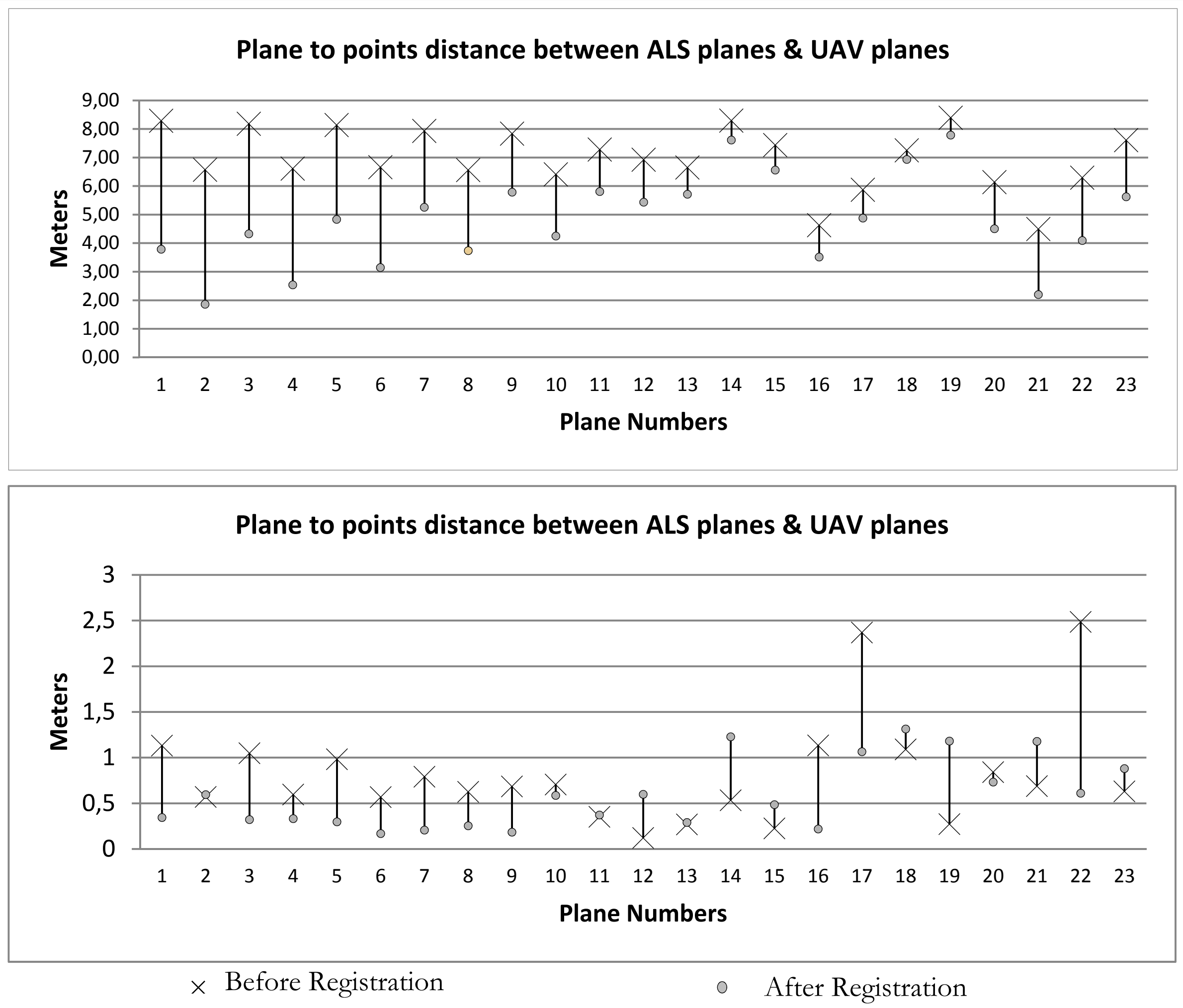


Figure 4.13: Impact of Vertical Shift application on residuals (mean) of Distance (above) shift not applied (below) shift applied

Sr. #	ALS Plane (ID no.)	UAV Plane (ID no.)	Sr. #	ALS Plane (ID no.)	UAV Plane (ID no.)	Sr. #	ALS Plane (ID no.)	UAV Plane (ID no.)
1	7	1098	9	301	371	15	1258	1028
2	15	2	10	333	951	-	1409	-
3	33	200	11	407	670	-	1458	-
4	45	203	11	442	665	16	1479	826
5	70	188	13	504	652	-	1819	-
6	81	198	-	517	-	17	1870	579
7	159	352	14	998	70	18	1885	541
8	183	349	-	1157	-			

Table 4.9: Final correspondences found within both datasets

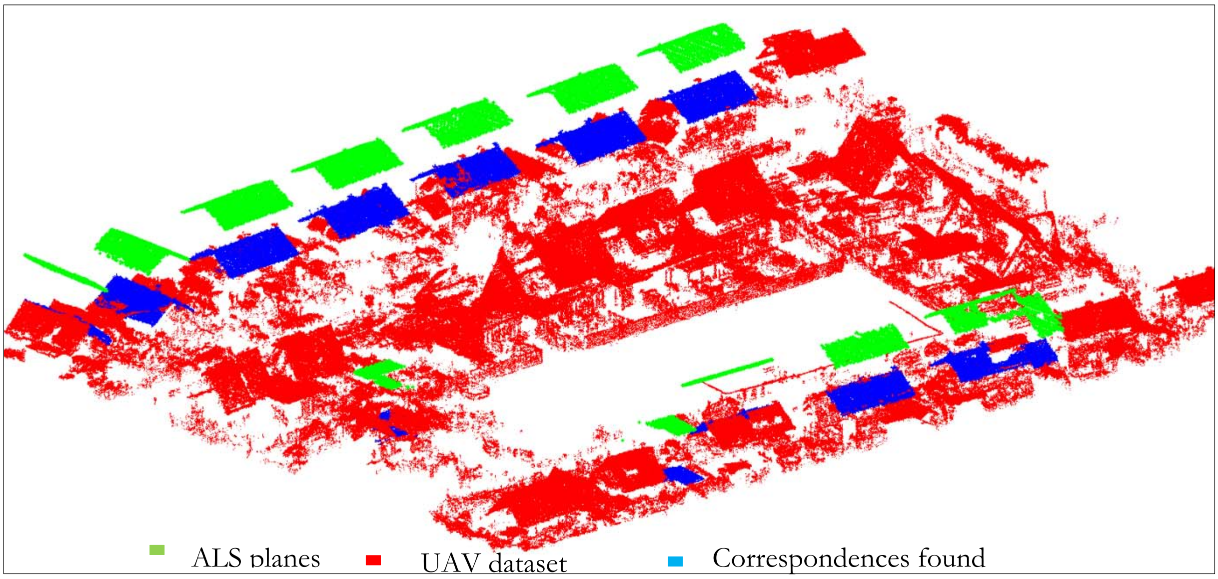


Figure 4.14: Final Matched Correspondences and their distribution in area

4.5. Registration Results

Plane-to-Plane Registration

Plane-to-plane rigid transformation is already involved in evaluation process of initial correspondences therefore each combination having true correspondences results in low residuals. Therefore combination having minimum residual (mean) is first exploited to compute transformation parameters using only three observations (matched pairs). Results of transformation parameters with three observations and all observations are shown in table 4.10 and 4.11 respectively.

Rotation parameter			Translation parameter		
Omega (degree)	Phi (degree)	Kappa (degree)	T_x (m)	T_y (m)	T_z (m)
-0.0280	-0.5151	-0.9071	-4.8612	3.5416	-0.9994

Table 4.10: Transformation parameters obtained with three observations

Rotation parameter			Translation parameter		
Omega (degree)	Phi (degree)	Kappa (degree)	T_x (m)	T_y (m)	T_z (m)
-0.3705	0.4703	0.1838	0.5664	1.8692	-0.2925

Table 4.11: Transformation parameters obtained with all eighteen observations

Point-to-Plane Registration

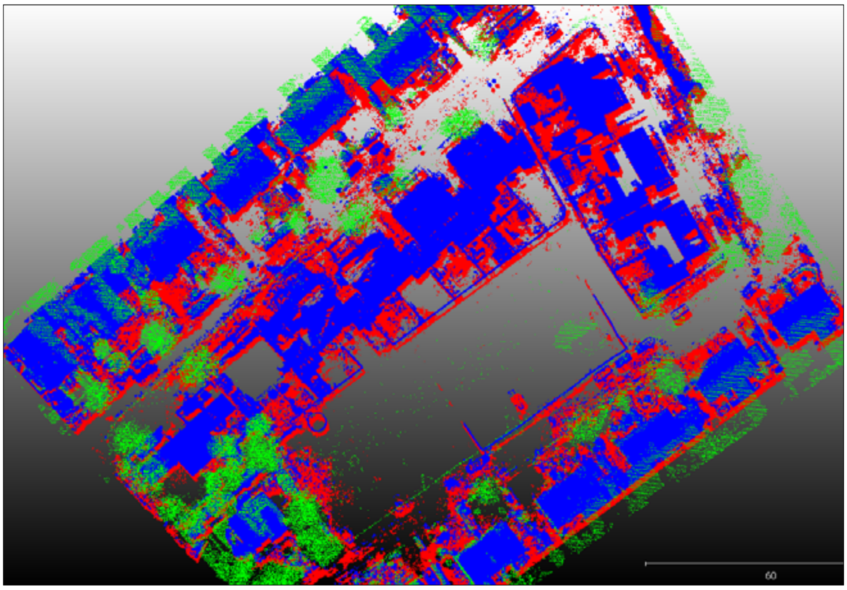
Second approach applied by exploiting all above correspondences is point-to-plane approach. Both rigid and non-rigid transformations are performed and results obtained in terms of parameter values are shown in table 4.12 and 4.13, respectively. Before applying point-to-plane approach, target dataset is renormalized to its actual position by removing applied vertical shift. Visualization of registration is presented in figure 4.15.

Rotation parameter			Translation parameter		
Omega (degree)	Phi (degree)	Kappa (degree)	T_x (m)	T_y (m)	T_z (m)
-0.1822	-0.0417	-0.1971	-0.4581	1.1208	8.0330

Table 4.13: Results of point-to-plane rigid transformation approach

Rotation parameter			Translation parameter			Scale
Omega (degree)	Phi (degree)	Kappa (degree)	T_x (m)	T_y (m)	T_z (m)	S (m)
-0.1398	-0.0206	-0.2381	-0.3898	0.9402	8.0554	1.0042

Table 4.14: Results of point-to-plane non-rigid transformation approach



ALS dataset UAV transformed dataset UAV original position

Figure 4.15: Registration result of point-to-plane approach

4.6. Conclusion

Feature based registration of point cloud starts from pre-processing of data. Pre-analysis and pre-processing are discussed in detail and plays a basis and vital role in registration process. Normalization of datasets is also necessary to overcome numerical instability occurs during feature extraction through RANSAC. Feature correspondences extracted from distance and angle constraints cannot be considered as true one in urban environment due to similar geometry issues. Plane-to-plane approach is applied for evaluation of these correspondences and vertical shift is also required for this. Correspondences extracted after rigid transformation are considered as confirmed to be used for registration process. Wrong correspondence may not hamper registration process but decreases registration accuracy. Results of plane-to-plane and point-to-plane approaches are given, however their accuracy will be discussed in next chapter with different cases.

5. PERFORMANCE EVALUATION

This chapter includes discussion on results obtained from implemented algorithm in last chapter. Evaluation of performance of algorithm is analysed by adopting few certain conditions and obtained results are discussed also. Systematic evaluation is performed and discussed by applying conditions. Pre and post registration analysis is also an important part of algorithm evaluation. Accuracy assessment is done with quantitative and qualitative analysis showing feasibility of algorithm. Limitations of adopted algorithm are discussed and conclusions drawn are added at end of this chapter.

5.1. Completeness, Correctness, Quality and Accuracy

Evaluation of algorithm is important to determine its effectiveness and limitations. Qualitative and quantitative measures are adopted for evaluation of performance/quality of this algorithm. Presence of wrong correspondences in final correspondence results may not hamper the registration process but can affect accuracy of registration. Quantitative and qualitative measures are adopted here to analyse quality of algorithm and registration, respectively.

To check quality of algorithm quantitative measures based on amount of observations/material are described as an efficient way of performance analysis (Heipke et al. (1997); Rutzinger et al. (2009) and Kourosh Khoshelham et al. (2010)). Critical review is presented by Rutzinger et al. (2009) about evaluation of performance of classification algorithm and Kourosh Khoshelham et al. (2010) have described different quantities for performance evaluation involved in quantitative analysis. Some of these quantities are presented and modified according to conducted research and are defined as under;

True Positive (TP): 'Number of corresponding pairs found in Reference and final matched pairs'.
True Negative (TN): 'Number of corresponding pairs which are found neither in Reference pairs nor in final pairs'.
False Positive (FP): 'Number of corresponding pairs found in Reference pairs with wrong corresponding pair in final pairs'.
False Negative (FN): 'Number of corresponding pairs found in Reference pairs but not found in final pairs'.

Or in tabular form;

	Referenced Pairs	Final Pairs
True Positive (TP)	√	√
True Negative (TN)	-	-
False Positive (FP)	√	×
False Negative (FN)	√	-

Table 5.1: Rules for Evaluation quantities

These quantities are further exploited for derivation of several metrics explained by different authors (Heipke et al., 1997; Kourosh Khoshelham et al. (2010); Rutzinger et al., 2009) for assessment of algorithms. Only few of those metrics are selected for assessment of proposed algorithm. Their definitions and mathematical relationships as described by Heipke et al. (1997) are presented on next page.

- Completeness: is termed as percentage of reference data which is presented in the final data. For example, number of planes retrieved back as final matched plane also is representing completeness of algorithm. Its optimum value is 1.

$$\text{Completeness} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5.1}$$

- Correctness: is measurement of percentage of correctly extracted features. For example, planes extracted as final matched planes also correctly found in reference data. Its optimum value is 1.

$$\text{Correctness} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5.2}$$

- Quality: is a measure of 'goodness' of final output. Completeness and correctness both metrics are involved in quality measurement. Its optimum value is 1.

$$\text{Quality} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}} \tag{5.3}$$

- Overall Accuracy: is measure to analyse overall accuracy of algorithm by considering all features used/not used for final registration. Its optimum value is 1.

$$\text{Overall Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{5.4}$$

5.2. Evaluation

Evaluation of adopted algorithm is executed through quantitative and qualitative analysis. For quantitative analysis, above mentioned metrics are computed for each case and for qualitative analysis, statistical analysis of residuals obtained after registration is considered. Quantitative metrics results are depicted in table 5.2 which are computed on results obtained in previous chapter. Rutzinger et al. (2009), have stated that high completeness and correctness are signs of a good algorithm.

		Completeness	Correctness	Quality	Overall Accuracy
TP	18	0.79	1	0.79	0.79
TN	0				
FP	0				
FN	5				

Table 5.2: Quantitative metrics results for developed algorithm

Table 5.2 shows quantitative analysis of adopted algorithm with completeness rate of 0.79 and correctness 1. Both metrics are representing high values therefore algorithm works fine with given datasets. No wrong matched pairs come in final matching pairs, therefore correctness remains 1, which shows effectiveness of this algorithm for particular datasets which are coarsely aligned to each other. Results of simulation of datasets are stated later on.

After quantitative analysis of adopted algorithm, qualitative analysis using statistical residuals is performed. An important objective of this research is to see reliability of feature-based matching approach as a potential alternative to sensor orientation techniques. This can be analysed by looking at residuals obtained after each case.

	Before Registration		After Registration			
			GCP based Registered dataset	Feature Based Registered dataset		
	Without vertical shift	With vertical Shift		Plane-to-plane (rigid)	Point-to-plane (rigid)	Point-to-plane (non-rigid)
Mean	6.5756	0.9234	0.1558	0.6299	0.2084	0.1959
Std. deviation	0.2864	0.3501	0.1840	0.3410	0.2430	0.2207

Table 5.3: Summary of Residuals results for Feature-based & GCP based point cloud

Distance residuals between ALS plane and corresponding UAV points are computed for evaluation of registration accuracy. Distance mean residual and standard deviation for different approaches are displayed in table 5.3. Important comparison can be made between residuals of point-to-plane non-rigid approach and UAV point data with GCP's. For this UAV's image based point cloud with ground control points has been pre-processed (surface growing) and then corresponding point-plane distance is computed with ALS dataset. Residuals of distance between ALS dataset and UAV dataset with GCP are shown in table 5.3. Values shown in table 5.3 are for whole dataset (all corresponding planes) and are different depending upon their approach. However GCP based point data has lowest mean residual of 15 cm showing its best fitness among others (Fig. 5.1). Point-to-plane approach has almost residuals near to GCP based UAV data with a difference of 4cm. This small difference proves that feature-based matching approach can be a reliable alternate to ground control method. These can be further analysed by histograms for each case.

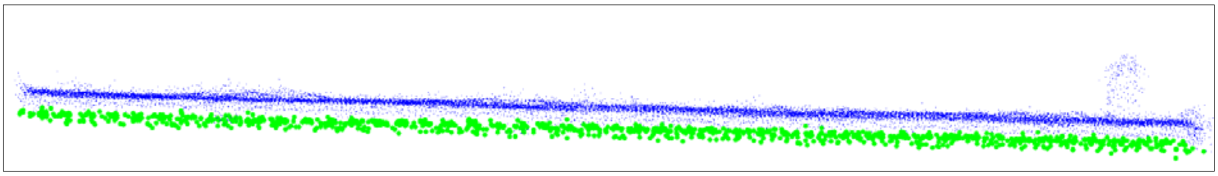


Figure 5.1: ALS (green) plane with UAV (blue) plane (ground control points used)

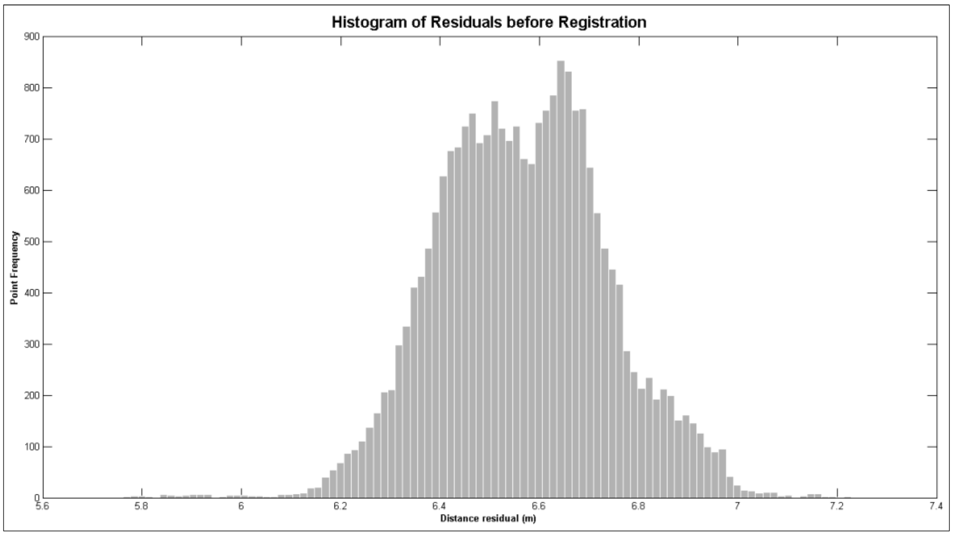


Figure 5.2: Distance residuals before registration

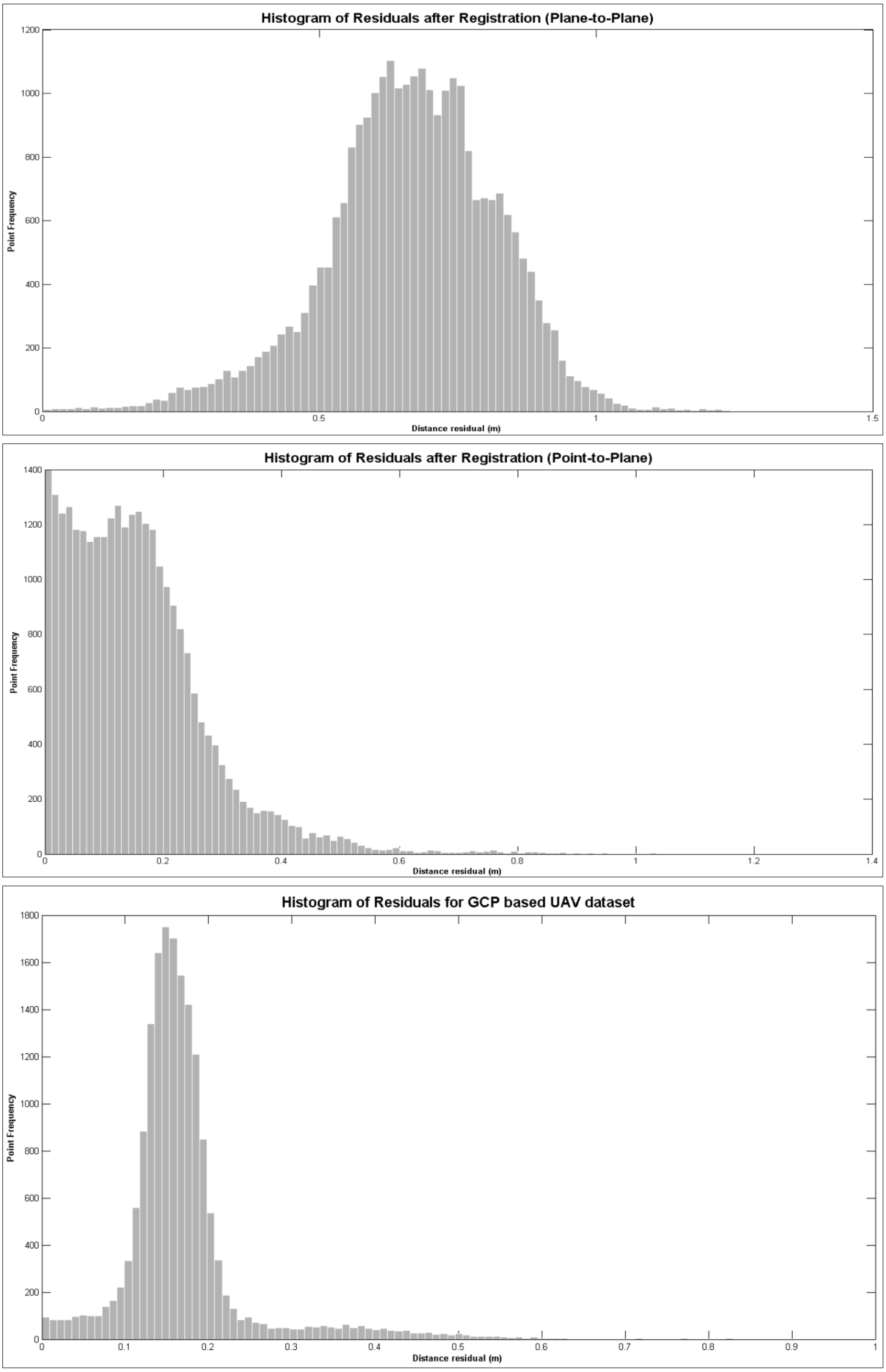


Figure 5.3: Distance residuals after registration with different approaches

Histograms of distance residuals before registration and after registration are displayed in fig. 5.2 and fig. 5.3, respectively. Absolute distances have been calculated for distance residuals therefore histogram of point-to-plane registration is skewed.

5.2.1. Systematic Evaluation

To further assess robustness of developed algorithm, artificial systematic evaluations are performed. Translation and rotation are applied to one dataset and both kind of analysis is performed for results obtained after adopted algorithm. For said purpose, three cases are performed which are discussed here;

Translation Case:

For translation case, UAV dataset is further shifted 5 meter away from its original position in each direction. Distance threshold value is also changed according to estimated distance. Final correspondences are achieved after adopted algorithm. Quantitative metrics results are shown in table 5.4.

		Completeness	Correctness	Quality	Overall Accuracy
TP	17				
TN	0	0.74	1	0.74	0.74
FP	0				
FN	6				

Table 5.4: Quantitative metrics results for Translation case

Completeness of algorithm is decreased but correctness remains 1. Quality and overall accuracy of algorithm also decreased. Translation more than 5 metre are also tested but gives wrong results, which means that algorithm is working fine upto 5 meter translation. Final correspondences have been determined between ALS dataset and newly translated UAV dataset. Appropriate threshold values are adopted to find initial and final correspondences. These final correspondences which are decreased in this case are exploited for computation of transformation parameters. Results of residuals before and after registration are shown in table 5.5. For plane-to-plane approach, translation parameters are not as accurate as in case of point-to-plane. Since plane-to-plane is sensitive with translation effects which reduces its accuracy as well. Point-to-plane approach shows much better results than plane-to-plane approach. Residual mean value and standard deviation for this approach also remains higher than point-to-plane approach. Quality of registration with point-to-plane approach for translation case seems reliable however quality of algorithm decrease in terms of quantitative metrics measures.

	Before Registration	After Registration	
		Plane-to-plane	Point-to-plane
Mean	3.9603	0.8913	0.2052
Std. deviation	0.1310	0.4340	0.2280

	Rotation parameters			Translation parameters		
	Omega (degree)	Phi (degree)	Kappa (degree)	T_x (m)	T_y (m)	T_z (m)
Plane-to-plane	0.0772	-0.0942	0.0442	5.8728	7.3573	6.1287
Point-to-Plane	0.0597	-0.0265	0.0647	5.4447	5.5054	5.2831

Table 5.5: Residuals and Registration results for Translation case

Rotation Case:

In second example, UAV dataset is rotated about 5 degree about its original position. Rotation is applied in each direction and translation remains constant. Correctness still remains 1 but completeness of algorithm decrease (Table 5.6). Algorithm gives more true positives if less than 5 degree rotation is applied. Decreasing number of final pairs also affect accuracy of registration and residuals are slightly on higher side as compared to original ones. This result shows that algorithm is sensitive with rotation also. Algorithm gives fine results if rotation is applied upto 3 degree.

		Completeness	Correctness	Quality	Overall Accuracy
TP	15	0.65	1	0.65	0.65
TN	0				
FP	0				
FN	8				

Table 5.6: Quantitative metrics results for Rotation case

	Before Registration	After Registration	
		Plane-to-plane	Point-to-plane
Mean	3.2052	1.0042	0.2276
Std. deviation	0.2288	0.7400	0.2341

	Rotation parameters			Translation parameters		
	Omega (degree)	Phi (degree)	Kappa (degree)	T_x (m)	T_y (m)	T_z (m)
Plane-to-plane	-3.6502	-4.2486	-4.1157	0.6401	0.1805	-1.5321
Point-to-Plane	-2.9106	-3.2458	-3.0924	0.5723	0.2413	-1.1129

Table 5.7: Residuals and Registration results for Rotation case

Rotation & Translation Case:
By analysing previous two cases, completeness of algorithm is decreasing, therefore for rotation and translation case UAV dataset is moved only three meter further away from ALS dataset and three degree rotated in all direction. After application of rotation and translation, final correspondences are determined by applying adopted algorithm. Final correspondences in this case achieved are 16 which are then used for computation of transformation parameters. To keep correctness of algorithm as 1, appropriate threshold values are adopted for correspondence search. For this case, completeness of algorithm is 0.69 with correctness 1 (Table 5.8). Transformation parameters achieved through these correspondences are described in table 5.9 and point-to-plane approach provides much better results than plane-to-plane approach.

		Completeness	Correctness	Quality	Overall Accuracy
TP	16	0.69	1	0.69	0.69
TN	0				
FP	0				
FN	7				

Table 5.8: Quantitative metrics results for Rotation & Translation case

	Before Registration	Estimated parameters After Registration	
		Plane-to-plane	Point-to-plane
Mean	3.4584	1.7590	0.2184
Std. deviation	0.1139	0.2521	0.2300

	Rotation parameters			Translation parameters		
	Omega (degree)	Phi (degree)	Kappa (degree)	T_x (m)	T_y (m)	T_z (m)
Plane-to-plane	-4.0715	-2.6015	-3.7446	1.9710	2.6930	-2.2556
Point-to-Plane	-3.2593	-2.8934	-3.1824	-3.4293	-2.5074	-3.0591

Table 5.9: Residuals and Registration results for Rotation & Translation case

All above discussed simulations shows limitations of developed algorithm. Initial hypothesis about datasets is that they are coarsely aligned to each other within range of 1-2 meter. Shifting UAV dataset further away from ALS is contradictory to hypothesis therefore algorithm works with low accuracy/completeness. Similarly UAV dataset is well aligned to ALS dataset in terms of rotation (results of table 4.14). In all three discussed cases, point-to-plane approach seems more reliable than plane-to-plane approach and transformation parameters estimated by point-to-plane approach is more realistic. However slight difference can be seen also in parameters due to noise found in both datasets. Both datasets are point cloud datasets and contain systematic and random errors which are also problematic when large translation or rotation values are applied. Artificial simulation has also been tested for ALS dataset only and achieved results were much better. But these cases are discussed here only to figure out robustness and limitations of developed algorithm.

5.3. Conclusion

Quantitative and qualitative tests are performed on given datasets. Qualitative analysis results show that registration occurs correctly between ALS and UAV datasets. Distance residuals (mean & std. deviation) and histograms for each approach depict quality of registration. Quantitative metrics for registration of given datasets are quite high. Algorithm attained completeness of 0.79, correctness of 1 and accuracy of 0.79. Algorithm has been further evaluated with the help of artificial simulation of datasets by shifting and rotating UAV dataset upto some extent. However, for simulated tests, limitations of algorithm are defined. For simulation cases, algorithm keeps its correctness as 1 but loses its completeness. This decreases overall accuracy of algorithm for simulated cases. Therefore it means that algorithm works fine with datasets which are well-aligned (<3m) to each other. Algorithm keeps its correctness as one by removing all wrong correspondences from final pairs but loses its completeness with large distances and angle differences.

Two type of feature-based approaches are analysed i.e. plane-to-plane and point-to-plane. Point-to-plane approach is found more robust than plane-to-plane approach in this study. Accuracy of point-to-plane is found higher than plane-to-plane approach. Their accuracy is analysed through distance residuals (mean & standard deviation). Point-to-plane non rigid transformation accuracy is compared with UAV data having GCP's and only difference of 4-5 cm is observed between their mean values. This result proves that feature-based matching approach has potential to become alternate of GCP's.

Based on above stated facts, it can be concluded that automatic feature-based matching (point-to-plane approach) produces satisfactory results and can be an alternate to GCP method. However it depends upon application. Accuracy achieved through feature-based method is highly dependent on used datasets accuracy, pre-processing quality and feature extraction process. Wrong estimation of these errors can lead registration process off track.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

Point data of topographic scene can be generated through high resolution images obtained by UAV photogrammetric systems. These high resolution images are processed by commercialized softwares for creation of point data. Payload capacity limitation of UAV's reduces possibility of mounting a precise GPS with IMU for direct georeferencing of its data. Indirect sensor orientation is another option for this purpose. Both these methods are reliable for removing 3D similarity shifts occurred due to above mentioned factors but are not cost effective. Point cloud data of urban scene generated through UAV images contains several features with regular geometry. These features include lines, planes, spheres, etc. and can be exploited for automated registration of both datasets. Conducted research is about to know reliability of feature-based registration of UAV's image based point cloud data with highly precise ALS point cloud data for removal of shifts without GCP's.

Key objective of this study is development of an automated algorithm which detects reliable correspondences, validate them and extract optimized transformation parameters for both datasets. These parameters are than exploited to register both datasets of topographic scene of same area. Algorithm consists of two steps: first step is about extraction and confirmation of correspondences and second step is exploitation of these correspondences for estimation of transformation parameters. Given datasets are then registered by using these estimated transformation parameters by applying plane-to-plane and point-to-plane approaches. Authentication of algorithm had been done by analysing outcomes obtained by data simulation. This research has recognized that feature-based matching (point-to-plane approach) is reliable to become an alternate method for 3D similarity transformation issue. Few conclusions during processing and development of algorithm are specified and are described as followings;

- Pre-processing (especially surface growing process) quality is vital for feature-based registration. Poor quality of segmentation process can remove many planar features from scene and also hamper feature extraction from point clouds.
- Plane parameters are extracted during plane extraction through RANdom SAmple Consensus (RANSAC) algorithm, which brings numerical instability in results, therefore datasets should always been normalized prior to start of registration process.
- Adoption of 'one-to-many' correspondence approach seems more realistic and reasonable as compared to 'one-to-one' in urban environment. 'one-to-one' approach might discard many correct correspondences also.
- A residual analysis based selection of final matching planes is robust enough for detection of wrong correspondences. Initial correspondences based on distance and angle constraints are not taken as true correspondences because of symmetrical geometries found in close neighborhood.
- Although three planes are enough to compute transformation parameters between two datasets but redundancy of planes is helpful in exploiting least square adjustment for optimal computation of transformation parameters.

6.2. Answers to research questions

1. Which technique has been used for feature extraction and is it reliable for registration?

A well-known algorithm RANdom SAmple Consensus (RANSAC) has been used for feature extraction (plane feature0. This algorithm is robust enough to deal with noisy datasets (especially in case of UAV point cloud dataset) and can handle noise upto 50%. However, it has few drawbacks e.g., slight change occurs at each run in plane parameters which affect results for datasets having large difference from origin.

2. Which kind of matching approaches are more robust for registration?

Two type of matching approaches have been applied for registration of both datasets i.e. plane-to-plane & point-to-plane, etc. According to performance evaluation of both these approaches point-to-plane approach is found more robust than plane-to-plane approach. Plane-to-plane is sensitive with large distance (>3 meter) between datasets and especially in dealing with noisy datasets having scale issue also, whereas point-to-plane approach is robust with noisy point datasets also. Non-rigid transformation through point-to-plane registers both datasets with high accuracy (in terms of residuals). It shows that point-to-plane feature matching approach can play an alternate role for indirect sensor orientation.

3. How far registration algorithm, reliably registers both datasets by using extracted/matched features?

Developed algorithm works fine with both matching approaches but accuracy obtained for both approaches is different. Accuracy obtained by point-to-plane approach is much better than plane-to-plane approach. Non-rigid point-to-plane approach reaches upto 4cm difference in residuals with GCP based UAV point dataset.

4. How robust this approach will be when the scene (features) changed considerably between both datasets?

Developed algorithm is tested on city data with a time scale difference of 5 years and scene has considerably changed due to urban expansion or some other development activities in target area. UAV data has up-to-date information about scene which is clearly visible in figure 1.1 showing some new buildings located in middle of area in UAV dataset (red colour). Un-availability of source plane (ALS dataset) in this middle area is not considering any planar feature within this region. By coincidence, in tested case, algorithm works fine as dispersion/scattering of planar features is not disturbed because developed area is in middle but it can reduce matching accuracy if same thing happens in some corner at large extent. However, no final conclusion can be made without applying developed algorithm on other dataset with structural deformation.

6.3. Recommendations

Few recommendations have been made for improvement of registration algorithm efficiency and accuracy or for future developments. Recommendations are;

- Rapid developments in UAV photogrammetry can also be exploited for further study. Instead of generating point cloud from UAV images (introduction of random errors), lidar-UAV photogrammetric system can also be used which can provide at least less noisy data than UAV image-based. Such type of lidar-UAV's are already come into play e.g. Wallace et al. (2012) has already used it for development of forestry inventory. Lidar-UAV data can also be exploited for conducted research and then evaluation results could be much better than now.
- This study considers only planar feature for registration of both datasets. Other features like 'line' can also be incorporated for more optimal results.
- Plane-to-plane rigid transformation is applied to dataset which is not working fine, however plane-to-plane non-rigid transformation results should also be analysed.

- Tested area is not congested area and buildings are situated at a quite noticeable distance from each other. It will be interesting to apply same technique with congested cities where extraction of true correspondence will become even difficult from this. This algorithm uses 1:5 correspondences which may become inefficient for congested urban areas.
- Adopted algorithm find true correspondences by inspecting matched correspondences after rigid transformation for their confirmation. Combination approach makes algorithm computationally expensive. In future it can be modified by looking only at residuals (mean & std.dev) of distances for each combination by applying few limitations/constraints in this approach.

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