Segmentation of Coloured Point Cloud Data

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by

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Abstract

Segmentation is a method which groups points based on certain similarity. This is required for information extraction from unstructured laser point cloud data. Many studies have been done on segmentation of point cloud data. The algorithms which are designed to extract planar surfaces, most commonly found surface in man made objects, group points exploiting the mathematical representation of the planar surface. This is because point clouds do not have any explicit information about the object except its 3D positional information. Recently, laser scanning systems also provide colour information as Red, Green and Blue (RGB) channels to each point in addition to the 3D coordinate in simultaneous capturing process. Likewise, there is growing interest to capture images from cameras and 3D points from laser scanner and map colour to each points registering both in same coordinate system. As colour is considered important cue for object recognition, this research is motivated to develop a segmentation algorithm which is able to create planar surface utilizing both location and colour information.

The segmentation methods proposed in literature are reviewed following the study of colour information. A segmentation strategy is devised in such a way that geometrical and colour information are combined in a single step process. The proposed segmentation algorithm consists following steps. First, k-d tree data structure is prepared to support neighbourhood finding operation; then RGB colour is transformed to chosen colour space (CIEL*a*b*); finally, region growing based approach starts. This basically has seed plane selection and plane growing steps. Information of global region is utilized to test geometrical similarity and of local region for colour similarity measurement to reduce the effect of colour variation. Variation in point density is considered by using k-nearest neighbours constraint with distance in point neighbourhood definition. A vector median filtering process is employed as pre-processing step to remove small details and noise in colour.

In order to test the performance of the developed algorithm, three datasets (two terrestrial laser scanning and one airborne laser scanning) are processed with optimised parameters. The reference segments are prepared interactively considering various object surfaces present in the data. A performance evaluation framework is defined to compare the results with the reference segments. This includes various metrics indicating the number of instances of correctly detected segment, over-segmentation, under-segmentation and noisy segments including the geometrical accuracy of the extracted planes. The performance is also evaluated by reducing the point density of the datasets.

The results are first evaluated based on visual examination. Then, more detailed quantitative evaluation is performed. The combination of geometrical and colour information has been able to produce more meaningful segments. The use of colour information has some adverse effects on the segmentation. The variation of colour on object surface, effect of shadow and the presence of additional objects tend to create inappropriate segments. The performance of the algorithm varies with the point density of the dataset. In general, lower the point density; lower the number of correct segments algorithm produces.

Key words: Laser scanning, coloured point clouds, segmentation

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1. Introduction

1.1. Motivation and problem statement

Nowadays laser scanning systems are widely used to capture three dimensional information of natural as well as man made physical surfaces. Both airborne and terrestrial laser scanning systems provide highly accurate and dense 3D point clouds (Abmayr et al., 2004). Each point in the point clouds contains explicit three dimensional coordinates. The information contained in high density point clouds has been utilized in wide range of applications including creating digital elevation models, generating 3D city models and reconstructing trees (Vosselman et al., 2004). In addition, the terrestrial laser scanning (TLS) systems have shown promising applications such as reconstruction of buildings with detailed façade information (Pu and Vosselman, 2006). Terrestrial laser scanning data provides an opportunity to extract façade elements for detail building reconstruction which is hardly possible by airborne laser scanning (ALS) data. Some of the other applications include reverse engineering of industrial sites (Rabbani et al., 2006) , documentation of cultural heritage sites, architectural application (Lerma and Biosca, 2005) and engineering geology (Slob and Hack, 2004).

Automatic processing of point clouds is important for timely extraction of useful information. Grouping of points into regions or segments sharing similar spatial properties is one of the widely used approaches in laser data processing, which is commonly known as segmentation process. Segmentation is an early step in feature recognition (Pu and Vosselman, 2006; Vosselman et al., 2004). This step is crucial since accuracy of the subsequent processes depends on the accuracy of the segmentation result (Vosselman et al., 2004). Several algorithms have already been proposed to segment laser point clouds using the positional information. These algorithms have largely focused on the extraction of planar surfaces, usually in relation to the building reconstruction process (Filin and Pfeifer, 2006). Segmentation results have also been used as low level information in automatic registration of point clouds taken from different stations of terrestrial laser scanning systems (Dold and Brenner, 2004). In case of airborne laser scanning, these results are also used in classification as well as filtering of terrain to get improved results (Perera, 2007; Sithole, 2005; Tóvári, 2006).

Many studies have already been done on segmentation of point cloud data. Most of the segmentation algorithms are tailored to work with 2.5D surface model assumption. The results are also affected by noise and sensitive to the point density (Filin and Pfeifer, 2006). On the other hand, many segmentation algorithms require tuning of different parameters depending upon the nature of data and application (Rabbani et al., 2006). It is currently a challenge to design an algorithm which works with true 3D point clouds, performs equally well with airborne and terrestrial laser scanning data and is less sensitive to the noise.

Recent generation of laser scanners provide colour information in Red, Green and Blue (RGB) channels in addition to the positional information of each point in point clouds. This colour information is generally captured by using image camera and mapped into the point data (Abdelhafiz

et al., 2005; Abmayr et al., 2004; Przybilla, 2006). Only location information has been taken into consideration for the segmentation of point clouds by majority of the algorithms. Since coplanarity is set as the main criteria in current segmentation algorithms, they ignore the possibility of extraction of regions with different colour in one planar region. For example, walls of two joined buildings having different colours could be segmented into one region. Figure 1-1 shows the terrestrial laser scanning data in natural colour in the left side and segmented point cloud data based on geometrical information in the right side. If we compare the segmentation result with coloured point clouds, it is a typical case of improper segmentation as walls of three buildings is represented by one segment.

(a) (b)

Figure 1-1: Point clouds from terrestrial laser scanning (a) natural colour and (b) coloured segmented regions

1.2. Research identification

In automatic building reconstruction, each segment may be considered as a potential building feature. Pu and Vosselman (2006) use these individual segments to retrieve important properties like size, position, direction and topology of the building façade elements from terrestrial laser scanning data. They also couple feature constraint based on the human knowledge of the building to recognize and extract the building elements like wall, doors and windows. The recognition as well as the extraction of properties of the different building elements basically depends on the accuracy of the segments.

Nowadays, there is a growing interest in creating true coloured 3D point clouds (Abdelhafiz et al., 2005; Abmayr et al., 2004). Verbree et al.(2005) even goes one step further and store the coloured point clouds in the database. They also provide a method to derive panoramic images from the point clouds stored in the database. This integrated colour information can serve as an important attribute in data processing. As colour is an important cue in object recognition, this opens a new opportunity to process the laser point clouds. The colour information can be effective to separate different elements in a planar region. This may help to generate meaningful segments so that the relevant object properties can be extracted more accurately. As currently available segmentation algorithms work only on the geometrical information of point clouds, development of new algorithm to work with coloured point clouds is essential to exploit the benefit of additional colour information. On the other hand, the point density can vary substantially among datasets and is also not consistent within the same dataset (Belton and Lichti, 2006) . It is also interesting to investigate the performance of the same algorithm with different point density data.

The subsequent sections present the research objectives, research questions to be addressed to achieve the objectives, research approach and structure of the thesis.

1.2.1. Research objectives

The main goal of this research is to use colour information in the segmentation process of coloured point cloud data. This research comprises the following specific objectives:

(i) To develop a segmentation algorithm which is able to extract planar surfaces from coloured point cloud data using location and colour information

(ii) To assess the effect of point density on the performance of the segmentation using colour information

(iii) To explore the suitability and limitation of using colour information in segmentation process

1.2.2. Research questions

(i) What is the state-of-the-art of segmentation algorithms in detecting planar surfaces?

(ii) How to define colour homogeneity measurement criterion in point cloud data?

(iii) How can a segmentation algorithm be designed to extract planar surfaces by using location and colour information?

(iv) How does the developed segmentation algorithm perform on different point density data?

1.3. Research approach

To meet the objectives of this research project, a methodology has been set-up in structured way. The main steps followed are presented in Figure 1-2. This methodology primarily includes colour pre-processing, reference data preparation, preparation of the reduced point density dataset and segmentation algorithm design, algorithm implementation, and performance evaluation. These steps are further elaborated in subsequent paragraphs.

First, review of the segmentation algorithms already proposed for point cloud data are carried out. The different methods are discussed and grouped based on their general characteristics. This is followed by the review of colorimetric information.

In next step, a method to pre-process the colour information of point clouds is developed. Thereafter, design of a segmentation algorithm is achieved and discussed in detail.

The next part of this research is related to the data preparation work for the implementation of the algorithm. This basically includes the preparation of different point density data and the reference data.

The final part of this research is concentrated on evaluation of the results. These datasets are processed with optimised parameters. The results based on visual examination are discussed. A framework for quantitative evaluation is designed and the results are discussed in detail.

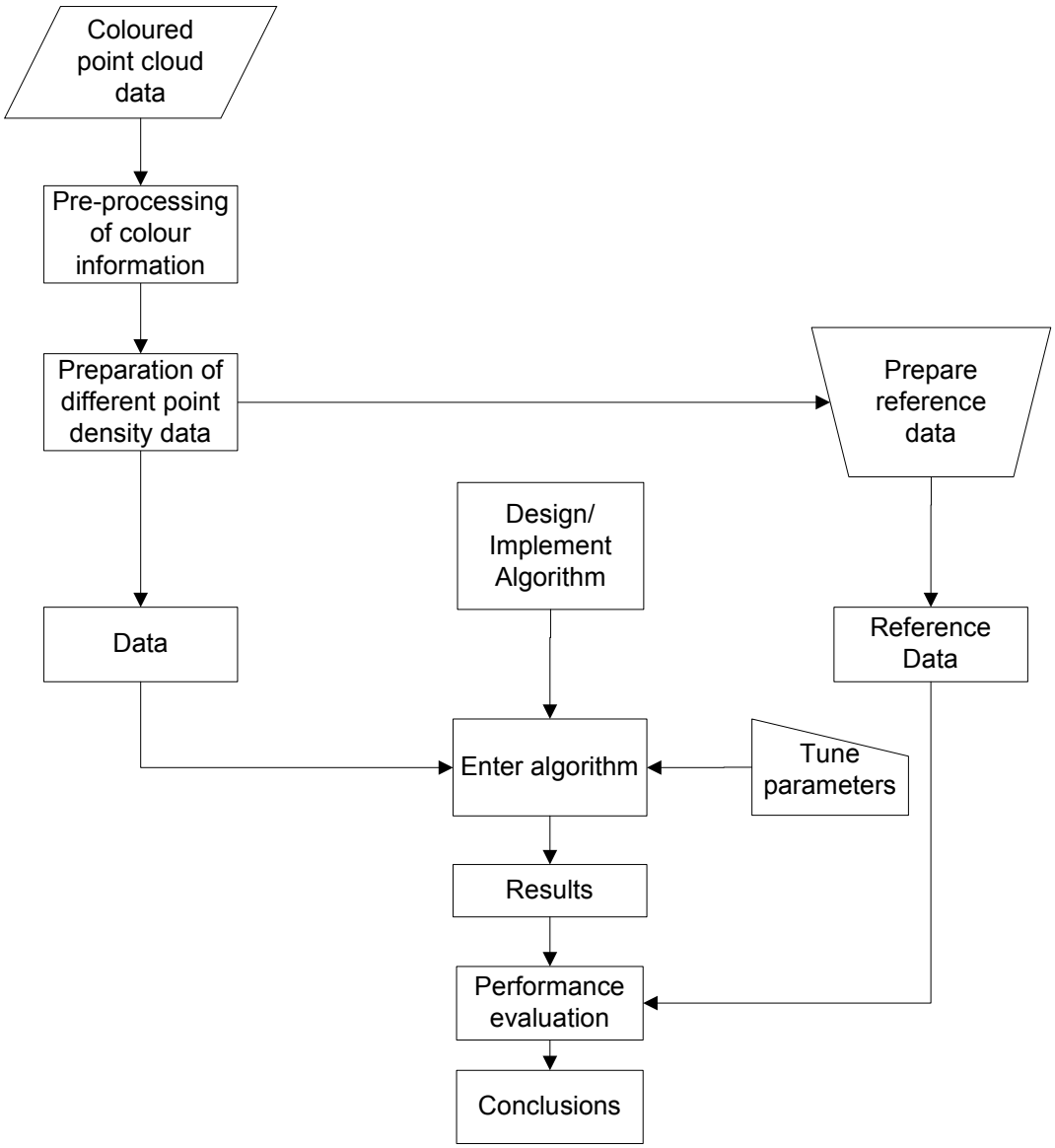


Figure 1-2: Research methodology

1.4. Structure of the thesis

This thesis is organised as follows, Chapter 1 introduces the research work and describes the objectives and the methodology whereas Chapter 2 reviews the literature about the segmentation of the point cloud data and classifies the approaches used in segmentation of planar surface from the point cloud. Furthermore, it provides information about colour representation and the metrics used for the colour similarity measurement. Chapter 3 is all about the algorithm development for coloured point cloud data. Chapter 4 provides information about the implementation of the algorithm. It describes the test datasets and presents the results. Furthermore, the discussion of the results based on the visual examination is provided. Chapter 5 reviews the performance analysis framework which is followed by the analysis of the developed algorithm with different datasets. Chapter 6 provides the conclusions and recommendations for future work.

2. Segmentation Methods and Colour Information

2.1. Introduction

As this research uses colour information in segmentation process, the main aim of this chapter is to review the segmentation methods and the colorimetric information from the literature. First, segmentation is introduced in section 2.2; then overview of segmentation methods developed for point clouds is presented in section 2.3. These methods are summarized in section 2.4. The study of colorimetric information is provided in section 2.5. This includes the study of colour spaces and different metrics used for colour similarity measurement.

2.2. Definition of segmentation

Segments are geometrically continuous elements of object surface that have certain similarities (Tóvári, 2006). Rabbani et al (2006) defines segmentation as the process of labelling each point in the point clouds so that the points belonging to the same surface or region are given the same label. In this process, points having similar features in continuous region are grouped to create a segment. Sithole (2005) expresses segmentation as:

$$\Theta P = \{\theta p \mid \forall p \in P\} \tag{2.1}$$

where ΘP is the segmentation operation in point clouds P and θp is the label assignment for a single point p in P. The results of segmentation are segments s having following properties:

- $S = \{s \mid s \subset P\}$
- $\Theta P \Rightarrow S$
- $\bigcup s_i = P \;\; where \; |s_i| > 0$
- $s_i \cap s_j = \varnothing \;\; where \; i \neq j$

This means, each segment s is a closed subset of point clouds P, the segmentation operator Θ determines the character of segment, every point in the cloud belongs to a segment and no two segments have points in common. Practically, the third property is not always valid for unstructured point cloud as there may be some points not assigned to any segments.

The homogeneity of segments

A segment is characterized by its homogeneity measured based on certain features. These features generally represent geometric properties, reflectance strength of laser pulse and spectral properties of the points belonging to that segment. Typically in laser scanning data, geometrical properties such as surface normals, gradients and curvature in the neighbourhood of a point are used. These are derived from the mass of points in the neighbourhood confirming the mathematical surface. The reflectance

strength of laser pulses i.e. intensity data, is rarely used in the segmentation process because of its noisy character (Tóvári, 2006). Mostly, only geometrical information has been used for segmentation of laser scanning data.

The homogeneity criterion is determined by the aim of segmentation which itself is governed by the application in hand. For example, planar surfaces are sought for building modelling purpose in which segment represents the part of building object such as roof or wall. The homogeneity criteria are set to confirm the parts of object are grouped to form a single segment i.e. tiles in roof are grouped to form a roof segment.

2.3. Overview of segmentation methods

Various algorithms have been proposed to detect planar surfaces from laser scanning data. Some of the relevant segmentation methods proposed for 3D point cloud data are discussed in this section. These methods aim to create homogeneous region present in point cloud data based on geometric criteria. The segmentation methods proposed in various literatures fall broadly into the following four groups:

1. Segmentation based on clustering of features
2. Segmentation based on surface growing
3. Segmentation by model fitting
4. Hybrid segmentation technique

After explaining the basic principles of above methods, some of the relevant algorithms proposed in each category are presented.

2.3.1. Segmentation based on clustering of features

In these algorithms, representative measures, so called features, are described first for each point based on the geometrical and radiometric characteristics. The features generally include position of each point, locally estimated surface normal, residuals of best fitting surface, and reflectance of laser scanning points. An n-dimensional feature space is constructed to map the n-features of each point. Thereafter, clusters are identified in the feature space. The points belonging to each cluster are labelled as unique segment in the object space. The result of this technique depends on the selected features and their derivation techniques as well as the methods used in partitioning the feature space. As features of individual points are generally described using points in local neighbourhood, this technique of segmentation is also sensitive to the noise in the data and is influenced by the definition of neighbourhood. Below is the description of a segmentation algorithm based on this technique.

Filin (2002) defines seven dimensional feature vector for each point. These features include position, parameters of a plane fitted to the neighbourhood of a point and the relative height difference between the point and its neighbours. Instead of creating 7-dimensional feature space, the author separates positional information to create 4-dimentional feature space. The feature space is clustered using unsupervised classification technique to identify the surface classes. After extracting surface classes, the points are grouped in object space utilizing spatial proximity measure.

2.3.2. Segmentation based on surface growing

In this approach, algorithm starts from a point and grows around neighbouring points based on certain similarity criteria. Vosselman et al (2004) describes this technique of segmentation which basically involves steps of identification and growing of seed surface:

Identification of seed surface:
A seed surface consists of group of neighbouring points that fits well in a plane. For seed surface selection, a group of adjacent points are identified and tested whether they fit well to the planar surface or not. If a plane is found to fit within some predefined threshold, it is accepted as seed surface; otherwise another point is tested.

Growing of seed surface:
Once seed surface is selected, every point in the seed surface is examined to find the neighbouring points that may fit to the plane defined by the points in the seed surface. This operation is basically intended to grow the surface towards its neighbourhood. The points are added in the growing surface if they meet the predefined criteria. After adding a point, the plane equation is updated. The decision of accepting a point to the plane can be based on one or more of the following criteria:

- *Proximity of point:* Only points that are within a certain distance from current seed surface are added to this surface.

- *Global planarity:* A candidate point is accepted in a segment if the orthogonal distance of a point to the plane formed by considering all the points already in a segment is within some threshold.

- *Surface smoothness:* To enforce this criterion, local surface normal for each point in the point clouds is estimated. A candidate point is accepted if the angle between the local surface normal of the point and the normal of the growing surface is below some threshold value.

Several variations in surface growing technique of segmentation are suggested in literature. Hoover et al. (1996) provides comparison of methods to find planar surfaces from the range images. These techniques mainly differ in the method or criteria used to select seed surface and in decision making during growing phase of the seed surface. Some of the segmentation algorithms based on surface growing are described below.

Rabbani et al. (2006) presents a method to segment unstructured 3D point clouds of industrial scene based on smoothness constraint. This method consists of two steps; local surface normal estimation and region growing. In the first step, normal for each point is estimated by fitting a plane to some neighbouring points selected using k-nearest neighbours or fixed distance neighbours. The author utilizes the residuals in plane fitting to approximate the local surface curvature. It is argued that the noise present in data or non-conformity of neighbouring points to planar model creates residuals in the plane fitting and can be considered as approximate curvature. These residuals are sorted and used to select seed points. The point with minimum residual is taken as the first seed point. The growing of

segment is performed by using previously estimated point normals and their residuals. In this phase, the points are added to the segment by enforcing proximity and surface smoothness criteria.

Tóvári and Pfeifer (2005) describe a segmentation method for airborne laser scanning data based on region growing, which is originally developed for terrestrial laser scanning. First, it uses k-nearest neighbours to estimate the normal vector at each point. Then a point is selected randomly and the adjacent points are examined for certain criteria. If the criterion meets, the adjusting plane is estimated using those seed points. During growing, the neighbouring points are added to the segment if they meet criteria of similarity in normal vectors, distance to growing plane and distance to current point. For plane adjustment, eigenvector/eigenvalue approach using the second moments of point coordinates are used. The authors mention that the plane is not parameterized over the xy-plane making it suitable for 3D point cloud data.

Another typical variation of region growing algorithm for airborne laser scanning data is presented by (Gorte, 2002). Triangles are used as basic surface units. The merging of triangular meshes is carried out by comparing the plane equation of neighbouring triangles. As triangulated irregular network (TIN) is used as basic surface element, it is only suitable for airborne laser scanning data where 2.5D surface assumption is most common.

2.3.3. Segmentation by model fitting

This method is based on the observation that many man made objects can be decomposed into geometric primitives like planes, cylinders and spheres (Schnabel et al., 2007c). This approach tries to fit primitive shapes in point cloud data and the points that conform to the mathematical representation of the primitive shape are labelled as one segment. Outliers caused by noise, registration errors or miscalibrations are frequently encountered in laser scanning point clouds (Schnabel et al., 2007c). Several robust parameter estimation methods have been proposed in literature, which are capable of extracting plane in the presence of outliers. The author mentions that over a number of methods proposed, Hough transform and Random Sample Consensus (RANSAC) are the most important. The underlying principles of these methods are described in the subsequent sub-sections followed by some of the proposed algorithm utilizing either of the methods.

2.3.3.1. 3D Hough transform

3D Hough transform allows direct detection of points that falls in a planar region by estimating parameters of the plane. Every plane can be represented by equation:

$$Z = s_x X + s_y Y + d \tag{2.2}$$

where s_x and s_y represent the slope of the plane along X- and Y-axis respectively and d denotes the distance of plane from the origin (0, 0, 0). Three plane parameters s_x, s_y and d define the parameter space, so called Hough space. Points belonging to a plane in object space also form a plane in parameter space maintaining the duality of two spaces (Vosselman and Dijkman, 2001). To detect a planar surface, each point in point clouds is mapped onto parameter space. The position in the

parameter space where most planes intersect represents the plane parameters in the object space. A notable problem in describing a plane in terms of slopes is that it approaches infinity as the plane approaches vertical. Since planes in 3D point cloud can be oriented in any direction, normal form of the plane equation is suggested (Overby et al., 2004).

$$\cos\theta.\cos\phi.X + \sin\theta.\cos\phi.Y + \sin\phi.Z = d \tag{2.3}$$

where $\theta \in \{0, 2\pi\}$ and $\phi \in \{-\pi/2, \pi/2\}$ denote two angles of the plane normal and $d \geq 0$ represents the distance from the origin to the plane (Figure 2-1). In this form of plane representation, the parameter space is represented by triplets of (θ, ϕ, d).

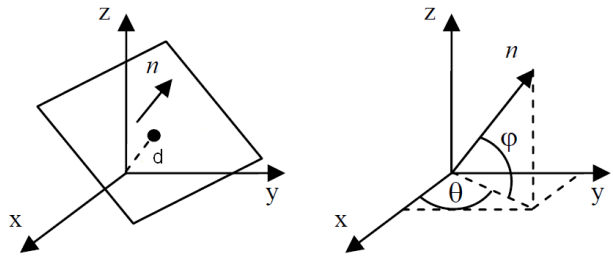


Figure 2-1: Parameterisation of plane (Overby et al., 2004)

In computer implementation, voting scheme is implemented to extract parameters of plane from discretized parameter space. For this, parameter space is discretized along three axes θ, ϕ and d into finite number of bins (θ_i, ϕ_j, d_k) such that $i \in \{0,1,...,N_\theta - 1\}$, $j \in \{0,1,...,N_\phi - 1\}$ and $k \in \{0,1,...,N_d - 1\}$ where N_θ, N_ϕ and N_d are the number of sampling along the axes (θ, ϕ, d) respectively. For each pair (θ_i, ϕ_j), a closest sampling value d_k is computed which contributes a vote to its corresponding bin (θ_i, ϕ_j, d_k). After every point has been mapped to parameter space, the parameters of planes (θ_i, ϕ_j, d_k) are extracted by selecting those bins that received a significant amount of votes.

In Hough transform, points contributing to the voting of a bin may not necessarily belong to the same plane in object space. Separate strategy, for example, proximity of points, is implemented to segment points that belong to a planar object face. The performance of Hough transform is dictated by the size of bins in parameter space. Therefore, parameter tuning is essential to keep balance between accuracy of the determined parameters and the reliability of the maximum detection of planes (Vosselman et al., 2004). Descriptions of some algorithms which are based on Hough transform are provided below.

Maas and Vosselman (1999) adopt 3D Hough transform for detecting roof planes in 3D point clouds. The Hough space is described by two slope parameters and a distance. This description of clustering space is only suitable for airborne laser scanning data as this form of equation can not describe vertical plane which is common in terrestrial laser scanning data. Vosselman and Dijkman (2001) also utilize Hough transform to detect roof planes. In addition, they used building ground plans and applied Hough transform inside the partitioned area of ground plans. They argued that the localized Hough transform helps to avoid the detection of false roof planes.

As mentioned earlier in this chapter, 3D Hough transform with normal form of plane equation is applied for automatic building reconstruction from laser and ground plan data by Overby et al. (2004). They first map all the points in the parameter space. To extract planes from parameter space, bin with the most votes is selected first and the corresponding points are evaluated based on the so called Projected Cluster-area Test. If the plane passes the test, the points belonging to the test plane are removed from the parameter space and the bin with the most votes is evaluated again. If test fails, evaluation is done to the second most voting bin and so on. While performing the test, all points are projected to the least square mean plane and grouped in clusters having mutual distance less than predefined threshold value. The area is computed by triangulating points in the projected plane with another angular threshold of triangle. A plane is accepted only if summed area of cluster is greater than certain value obtained from dividing the number of contributing points by a tuneable constant.

Vosselman et al. (2004) suggests a variation in Hough transform using surface normal to speed up the process of planar surface detection with increased reliability. The normal vector and the position of a point define a plane. The parameters of this plane can be directly mapped to a single point in the parameter space, thus avoiding the process of computing intersection of the plane with corresponding bin. Only the increment of counter of single bin is enough. The author claims that the use of normal vector information also reduces the risk of detecting false planes.

2.3.3.2. RANSAC

The Random Sample Consensus (RANSAC) paradigm is used for robust fitting of parametric model to the data that may contain high degree of noise and outlier. RANSAC generates a large amount of hypothesis of primitive shapes by randomly selecting minimum subset of sample points that each uniquely determines the parameter of a primitive (Schnabel et al., 2007a; Schnabel et al., 2007c). The scoring mechanism is employed to detect the best shape primitive.

While detecting plane, three points are randomly selected to estimate parameters of candidate plane. Then, the remaining points are tested to the candidate plane with some thresholds and score is given to the candidate plane based on the number of points that are within threshold distance to the plane i.e. inliers. If this score is greater than some threshold, the candidate plane is considered as the detected plane. Otherwise, above procedure is repeated keeping the record of plane with the highest score so far. After given number of trials, either the plane with most score is considered as the detected plane or reported as the failure.

Schnabel et al. (2007a) notes that the complexity of RANSAC is dictated by two major factors: the number of minimal candidates that are drawn and the cost of evaluating the score for every candidate plane. The number of candidates that have to be considered to extract the plane having highest possible score is governed by the probability that the best possible plane is indeed detected. The minimum number of trials (T) required to detect a plane with probability (p_t) is given as (Schnabel et al., 2007a).

$$T \geq \frac{\ln(1-p_t)}{\ln(1-\omega^3)} \tag{2.4}$$

where ω denotes the fraction of inliers.

The number of trials T can then directly be computed from the knowledge of p_t and ω. p_t is generally kept between 0.9 to 0.99 (Bretar and Roux, 2005; Tarsha-Kurdi et al., 2007). Problem arises from the fact that the proportion of inliers ω is often not known before hand. To address this problem, generally, an adaptive estimation technique is applied. At the beginning, relatively low estimate of ω is taken and the estimate is updated as the computation progresses. The value of ω can also be assumed from the data knowledge.

The subsequent paragraphs describe some algorithms based on RANSAC paradigm that are developed for the segmentation as well as primitive shape detection of laser scanning data.

Bretar and Roux (2005) propose an algorithm for the detection of roof facets of building based on normal driven RANSAC (ND-RANSAC). For this purpose, they first calculate the normal vectors for each point and then randomly select sets of three points having the same orientation of normal vectors. The number of random draws is managed automatically by statistical analysis of the distribution of normal vectors using the Gaussian sphere of the scene.

RANSAC based algorithm for the detection of several geometrical shapes such as plane, sphere, cylinder, cone and torus is presented in (Schnabel et al., 2007a; Schnabel et al., 2007b; Schnabel et al., 2007c). They use localized sampling strategy using octree data structure for the random selection of minimal subset of points. While evaluating the score of the candidate shape, number of points within the tolerance distance of shape, minimum deviation of surface normal and the connectivity of points are taken into account.

The extension of RANSAC algorithm for roof plane detection is proposed by Tarsha-Kurdi et al. (2007). They use number of trials as an input rather than probabilistic calculation. They suggest calculating it by using the point density and the foreseeable size of urban roof plane. Another adaptation over the standard RANSAC technique is that they use criteria of standard deviation of distance to plane and minimum number of point set instead of the large number of points to evaluate the candidate shape. They compare the performance of the algorithm with Hough transform and report that RANSAC performs better.

2.3.4. Hybrid segmentation technique

In this approach, more than one method is combined to detect planar segments. In general, region growing method is combined with other plane detection methods as it takes into account the spatial proximity of the points in more natural way. Some examples of hybrid method proposed for segmentation of 3D point clouds are presented in the subsequent paragraphs.

Oude Elberink and Vosselman (2006) use Hough transform for seed surface selection in their surface growing approach. For some arbitrary point, k-nearest neighbouring points are selected and Hough

transform is applied to only these points. If minimum numbers of points are identified to be in a plane by Hough transform, the least square technique is used to fit the parameters of the plane and the points are taken as seed surface. The acceptable seed surface is used here instead of the optimal seed surface (having maximum number of points with minimum residuals) in a cost of computation speed. In growing phase, the orthogonal distance of adjacent points to the growing plane is examined and the points are added to the surface if the distance is below some threshold.

Roggero (2002) combines hierarchical region growing and principal component analysis (PCA) to segment airborne laser data. PCA is used to define the aggregation criteria and to describe the geometrical properties of the surfaces. Two algorithms differing in PCA and in aggregation criteria are proposed. One of the algorithms is based on descriptor mapping. First, one or more properties like static moment, curvature or junction are computed and mapped to each point. Then the region growing is performed with reference to the property map. The pulse intensity is also considered in the feature space. The second algorithm does not perform descriptor mapping and uses PCA in region growing phase to realize faster method.

2.4. Summary of segmentation methods

The state-of-the-art of segmentation methods are provided in previous section 2.3. An attempt is made to group segmentation methods proposed by various researchers. Summary of these methods is provided in Table 2-1. Based on the review of these methods, some conclusions are drawn and presented in section 2.6.

Table 2-1: Summary of segmentation methods

Segmentation methods		Researchers	Description
Clustering		(Filin, 2002)	Seven dimensional feature space is defined to cluster points.
Region growing		(Vosselman et al., 2004)	Provides description of surface growing techniques.
		(Rabbani et al., 2006)	Utilises local surface normal similarity as a criteria to grow.
		(Tóvári and Pfeifer, 2005)	Uses surface normals, spatial proximity and distance to plane as criteria to grow.
		(Gorte, 2002)	Grouping of TIN, more suitable for ALS data.
Model fitting	Hough transform	(Vosselman and Dijkman, 2001)	Utilises slope form of plane equation to create 3D Hough space.
		(Maas and Vosselman, 1999)	Utilises slope form of plane equation to create 3D Hough space for roof plane detection.

Segmentation methods		Researchers	Description
		(Overby et al., 2004)	Utilises normal form of plane equation and uses Projected Area test to identify individual planes.
		(Vosselman et al., 2004)	Provides description of Hough transform. In addition, describe method of using surface normals in Hough space.
	RANSAC	(Bretar and Roux, 2005)	Utilizes local surface normal for each point, uses RANSAC selecting three points with similar orientation of normals.
		(Schnabel et al., 2007a; Schnabel et al., 2007b; Schnabel et al., 2007c)	Localized sampling strategy using oct-tree data structure Local surface normals, spatial proximity and number of points within the tolerance distance from shape are used in candidate evaluation.
		(Tarsha-Kurdi et al., 2007)	Uses standard deviation of distance to plane and minimum number of points as candidate evaluation criteria.
Hybrid		(Oude Elberink and Vosselman, 2006)	Hough transform for seed plane selection and then region growing based on the distance to plane criteria.
		(Roggero, 2002)	Combines PCA and region growing

2.5. Overview of colour information

To understand the use of colour in segmentation process, the colour representation technique is reviewed and presented. Various similarity measurement criteria proposed in literature for colour image processing are also reviewed.

2.5.1. Colour representation

Colour is considered as one of the most important properties that characterizes an object. Human perceive colour as a combination of three primary colour components: Red, Green and Blue. The representation of colour using these primary components is commonly known as RGB colour model. This model corresponds to the physical sensor of the coloured light and is implemented as red, green and blue filter in most CCD (charge coupled devices) sensors. There are other colour representation techniques commonly used in image processing and are derived from linear or non-linear

transformation of RGB colour. Overview of various colour spaces and their transformation to other spaces are provided by Skarbek and Koschan (1994), Cheng et al. (2001) and Lucchese and Mitra (2001). Some of the most widely used colour spaces are described below.

RGB

The RGB colour space can geometrically be represented in 3D cube using Cartesian coordinate system. This colour space is dependent of the intensity of colour. In a RGB cube, measurement of colour does not represent colour difference in uniformly, which restricts the possibility of evaluating the similarity of two colours by their distance in colour space (Cheng et al., 2001). This also does not resemble the perception of colour by human visual system.

HSI

The colour representation in terms of hue (H), saturation (S) and intensity (I) is closely resembles to the human visual system perception of colours (Cheng et al., 2001) and can be derived from RGB space as:

$$H = \arctan\left(\frac{\sqrt{3}(G-B)}{(2R-G-B)}\right) \tag{2.5}$$

$$I = \frac{R+G+B}{3} \text{ and } S = 1 - \frac{\min(R,G,B)}{I}$$

In this colour model, hue represents basic colour such as red or pink. Saturation describes the purity of colour i.e. amount of white light mixed with the hue. Intensity represents the brightness of colour. This has much interest because hue (i.e. colour) is independent of intensity or luminance. This colour representation is particularly useful where intensity varies due to change in illumination and extensively used in colour image processing. Beside its advantages, the problem of using HSI space is that at low saturation or low intensity, hue is imprecisely determined (Skarbek and Koschan, 1994) where intensity plays dominant role in distinguishing colour (Cheng et al., 2001).

CIE Spaces

CIE[1] has proposed perceptually uniform colour spaces which can be produced by transforming RGB colour triplets. The widely used colour spaces are CIEL*a*b* and CIEL*u*v*. Conversion from RGB to CIEL*a*b* can be carried out by using the following relations (Skarbek and Koschan, 1994):

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.607 & 0.174 & 0.200 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 1.116 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{2.6}$$

$$L^* = 116\left(\sqrt[3]{\frac{Y}{Y_0}}\right) - 16 \tag{2.7}$$

[1] International Colour Consortium (Commission Internationale de I'Éclairage)

$$a^* = 500\left[\sqrt[3]{\frac{X}{X_0}} - \sqrt[3]{\frac{Y}{Y_0}}\right]$$

$$b^* = 200\left[\sqrt[3]{\frac{Y}{Y_0}} - \sqrt[3]{\frac{Z}{Z_0}}\right]$$

Here, X_0, Y_0 and Z_0 are the colours of standard white and is taken as 255 in this research. L^* represents lightness, a^* approximates redness-greenness, and b^* yellowness-blueness. The main advantage of using this colour space is that the colour difference can be measured by using the geometrical distance in the colour space. Refer Skarbek and Koschan (1994) for the relation to convert RGB colour to CIEL*u*v*.

2.5.2. Colour similarity measurement

The measure of colour difference is one of the most important problems in colour distribution analysis. This measure depends on the type of colour space and the colour metric used in colour analysis (Tremeau and Borel, 1997). In colour image segmentation, there are numerous algorithm proposed based on the similarity measure of colour in a region. Different similarity measures are used in literature based on the colour space and the application in hand (Wesolkowski, 1999). Often, problems of separating objects with shadows, highlights and texture are encountered. In segmentation, reducing of dependency to change in lighting intensities is desirable. Suitable choice of colour space can handle this problem to some extent. The use of HSI space in colour image segmentation is fairly common (Cheng et al., 2001).

The Euclidean distance based measure is used in RGB as well as in CIEL*a*b* colour spaces. Let C_i is the colour of ith point in point clouds which is represented by colour triplets and $\wp$ is the distance computation function. The colour difference between two points P_i and P_j is given by the Euclidean distance as in equation below:

$$\wp_{Euc}(C_i, C_j) = \sqrt{\sum_{k=1}^{3}\left(C_{ik} - C_{jk}\right)^2} \tag{2.8}$$

Here, k represents the individual channel in colour triplets. Whereas, in HSI colour representation, the colour difference can be measured, as suggested by Skarbek and Koschan (1994), using the following relation:

$$\wp_{HSI}(C_i, C_j) = \sqrt{(I_j - I_i)^2 + S_j^{\,2} + S_i^{\,2} - 2S_iS_j\cos(H_j - H_i)} \tag{2.9}$$

As mentioned above, same distance in different position of colour cube does not represent the same colour difference in RGB space. However, some researchers have used RGB colour directly as it avoids the computation cost of transforming colour spaces and is the colour model used by many sensors. In region growing based segmentation, measure of colour similarity between the candidate

point and growing seeded region is required. This can be done by measuring the distance between the candidate point and the mean colour of the region which has been applied by Tremeau and Borel (1997) in their colour image segmentation problem. The Euclidean colour distance between ith point and the colour mean of the region is computed as:

$$\wp_{Euc}(C_i, \overline{C}) = \sqrt{\sum_{k=1}^{3} (C_{ik} - \mu_k)^2} \tag{2.10}$$

Where, $\overline{C}$ represents the mean colour of a region, which is defined by the triplets of mean μ_k computed for each colour channel ($k = 1, 2, 3$) of points. The mean of k th colour channel of a region having N points is:

$$\mu_k = \frac{1}{N} \sum_{i=1}^{N} C_{ik} \tag{2.11}$$

In segmentation process, however, the measure of colour of a region as a whole is important as colour value of a region is not uniform for most of the natural as well as man made objects. Chau and Siu (2004) use colour mean and variance criteria to decide while merging two adjacent regions in CIEL*a*b* colour space. They argue that the consideration of colour variance in addition to colour mean helps to maintain colour homogeneity of the region. The variance of kth colour channel is computed as:

$$v_{kk} = \frac{1}{N} \sum_{i=1}^{N} (C_{ik} - \mu_k)^2 \tag{2.12}$$

2.5.3. Colour image segmentation

Most of the laser point cloud data segmentation methods presented above has some root to the colour image segmentation. Cheng et al (2001), Lucchese and Mitra (2001) and Skarbek and Koschan (1994) provide the overview of the colour image segmentation methods. These authors have attempted to categorize the segmentation methods and these categories reveal similarity to the methods as explained above for the point clouds. On the other hand, majority of the segmentation methods for point cloud data as well as colour image have some root to the grey value image segmentation problem. Therefore, the methods are not elaborated here in details. It is noteworthy to mention here that another extensively used image segmentation technique is edge detection based method in which the edges are defined first and then the homogeneous region is sought inside the previously defined edges. However, the identification of colour edge in unstructured point clouds will not be a trivial task.

2.6. Concluding remarks

The overview of segmentation methods and colour information are presented in this chapter. The summary of reviewed segmentation methods are presented in Table 2-1. Based on the review of different segmentation methods, following conclusion can be drawn for each group of segmentation methods.

- The results of the segmentation process based on clustering of features are dictated by choice and the quality of the representative features of each point. Computationally, clustering multidimensional features for large data volume is very expensive. Dealing with large volume of data is obvious in laser scanning point clouds.

- As region growing based methods always consider the points in spatial proximity, this is considered as one of the desirable strengths of segmentation process. In the mean time, quality of results from region growing based segmentation depends on the methodology used for seed surface selection and the criteria applied for region growing.

- The segmentation based on planar surface fitting using Hough transform or RANSAC is effective in presence of noise and outliers. The straight forward implementation of both techniques is computationally inefficient. On the other hand, the plane detected by these techniques may not necessarily belong to the same object surface. To separate points belonging to one object surface from the points in detected plane, separate strategy should be employed.

- The hybrid technique has some desirable strength as it exploits the benefits of two or more methods. Combination of model fitting on local region then expanding towards adjacent points using region growing is one of the potential segmentation methods.

With respect to colour spaces, RGB colour space corresponds to the colour from physical sensors whereas HSI closely resembles human perception of colour. The CIEL*a*b* space is a uniform colour space. The metric to be used for colour similarity measurement entirely depends on the chosen colour space.

3. Proposed Segmentation Method

3.1. Introduction

The overview of the segmentation methods are presented in section 2.3, which is followed by the colour information in general. Before developing a segmentation algorithm, the approaches used to create coloured point clouds are presented in section 3.2 and segmentation strategies to use colour in segmentation are devised in section 3.3. A pre-processing step for colour information is introduced in section 3.4. Based on the devised segmentation strategy, an algorithm is proposed and described in detail in section 3.5.

3.2. Coloured point clouds

As the point clouds from the laser scanning systems does not bring any information about the colour of the object surface, separate camera is used to acquire the colour images of the objects. The colour of the object is transferred to the corresponding points in the point clouds by registering both in common coordinate systems. The approaches followed to create coloured point cloud data are summarized below.

- **Simultaneous capturing of points and images**

  In this approach, both the points and images are captured more or less at the same time. Some laser scanners have integrated colour camera (e.g. LMS-Z420i from RIEGL) or video camera (e.g. FLI-Map by Fugro-Inpark) as additional devices. These scanners provide the colour of the target object in addition to its positional information to each measurement. Another possibility is to mount separate colour image camera at the position known to the laser scanner. Particularly in terrestrial laser scanning systems, additional camera is mounted at the top of the laser scanner and colour information is mapped to each point in later stage. Figure 3-1 shows one of the basic set up of LMS-Z420i from RIEGL with mounted digital camera.

Figure 3-1: RIEGL scanner LMS-Z420i with mounted digital camera (Source: http://www.riegl.com/)

- **Independent capturing of points and images**
  The above technique has an important drawback of limiting the data capturing time. Abdelhafiz et al. (2005) argues that the best colour quality will be obtained at the best lighting conditions of the image which may not necessarily be at the same position of the laser scanner. This becomes even more important in case of terrestrial laser scanning systems where points are scanned from many positions and later registered them together in one coordinate system. Abdelhafiz et al. (2005) suggests an approach of capturing point data and images separately and later registering them together. After registration, the pixel colours are extracted from the images and fused with the points. In this approach, the quality of colour in points is also governed by the quality of the registration process.

3.3. Segmentation strategy

The primary research problem here is to combine the colour and geometrical information for the segmentation process. In this context, the desirable properties of the segmentation algorithms are:

- able to combine both colour and location information without dampening of one information by another
- able to detect all orientation of planes
- able to detect various sizes and shapes of segments
- less sensitive to colour variations
- robust and reliable in presence of noise and outliers

The geometrical space and colour space can be considered independent of each other, which permit to treat them separately. Another reason for considering both separately is that the geometrical information of laser scanning is richer than the colour information available in the data as colour captured in the natural environment is affected by illumination and shadows. This allows treating geometrical information as the first order information while allowing some colour variation on surface. Two segmentation strategies deemed suitable for coloured point cloud data:

1. Two step process where the point clouds are segmented first by using only geometrical information. The segmentation result is further analysed and re-segmented using the colour information. In re-segmentation process, the points that belong to a segment generated by the previous operation can be considered at a time. In this strategy, segmentation based on geometrical information is preferred at the first stage as it is considered first order information.

2. Single step process where geometrical and colour information are used together to create homogeneous planar surface.

The first strategy has some analogy with the problem of data fusion though the main objective of this research is to work with already integrated dataset i.e. coloured point clouds. In another approach applied by Bretar and Roux (2005) in their problem of hybrid image segmentation, point clouds data and aerial images are segmented separately. Then the regions in the image are merged by enforcing

constraint of planar primitives from laser segments and radiometric from images. In this approach, the error generated by one process is carried to successive processes. Here, the second strategy seems promising as it allows combining geometric and colour information together in a simultaneous process.

In addition, fine details and noise present in colour are undesirable in segmentation as they may lead to produce more segments. The use of filtering technique, commonly used in image processing, can be applied to reduce such effects in segmentation of coloured point clouds. This is explained in subsequent section as pre-processing step.

3.4. Pre-processing of colour information

Over variety of techniques suggested in literature to suppress fine details and noises in images, smoothing filters based on the local window around the candidate pixel are fairly popular. In case of colour image, common approach is to apply filter in three colour channel separately (Chau and Siu, 2004). This does not utilise the correlation between colour triplets (Vardavoulia et al., 2001). In order to preserve the inherent correlation that exists between three colour channels, the vector filtering algorithms are preferred (Lukac, 2003). The non-linear filter such as vector median filter is often applied in colour image smoothing and noise removal due to its property of edge preserving (Koschan and Abidi, 2001), which minimizes the sum of vector distances with other input multi-channel sample. The basic principles of vector median filters are described below as possible filtering technique. Then its adaptation to the point clouds data is presented.

Let C_i represents the colour vector of each pixels in local window with pixels set $\{C_i, i = 1, 2, ...n\}$ and n is the number of pixels in the window. If $\wp_i$ represents the dissimilarity measure corresponding to C_i :

$$\wp_i = \sum_{j=1}^{n} \left\| C_i - C_j \right\|, i = 1, 2, ..., n \tag{3.1}$$

where $\|....\|$ is an appropriate norm. A common choice of norm is L_1 -norm (Cree, 2004) and is given as:

$\left\| C_i - C_j \right\|_{L1} = \sum_{k=1}^{3} \left| C_{ik} - C_{jk} \right|$, here k represents the individual component of colour triplets.

Another popular representation is L_2 -norm or Euclidean distance and can be computed using equation (2.8). The vector C_i for which $\wp_i \le \wp_j, \forall j = 1, 2, ..., n$ is the output of the vector median filter. It means, this filter outputs the vector that minimizes the sum of the distance to all the other vectors.

Similarly, if the angle between vectors is used in dissimilarity measurement, the above filter becomes vector directional filter which can be expressed as:

$$\alpha_i = \sum_{j=1}^{n} A(C_i, C_j), i = 1, 2, ..., n \tag{3.2}$$

here, α_i corresponds to the vector C_i whereas $A(C_i, C_j)$ denotes the angle between vectors C_i and C_j. The angle between two vectors can be computed by using the relation:

$$\alpha = cos^{-1}\left(\frac{C_i \bullet C_j}{|C_i||C_j|}\right) \tag{3.3}$$

where $C_i \bullet C_j$ denotes the dot product of two vectors and $|C|$ is the magnitude of colour vector. The vector C_i for which $\alpha_i \leq \alpha_j, \forall j = 1, 2, ..., n$ is the output of this vector directional filter. In other words, this filter outputs the vector that minimizes the sum of the angles between all the other vectors.

The basic principle of vector filter can be adapted to smooth the colour information of point clouds. Instead of using pixels inside a local window of candidate pixel in 2D image processing, k-nearest neighbouring points to a candidate point can be used. For our work, vector median filter is considered as suitable filter as it is effective in removing intensity outliers (Koschan and Abidi, 2001) and is applied in RGB colour space. An algorithm is developed to smooth the colour of each point in point cloud extending the vector median filter described above. The L_1-norm is used to calculate the distance for computational simplicity.

3.5. Algorithm design

Looking at the segmentation methods and the strategy formulated above, region growing based algorithms allow treating geometrical and colour spaces separately. This is important for allowing some variation in colour on a planar surface while incorporating strict geometrical criteria. The region growing based method proposed by Vosselman et al. (2004) for planar surface extraction has some desirable strength to our problem of segmenting coloured point clouds. Hough transform is used for the direct detection of seed plane in the vicinity of arbitrarily selected seed point and it is grown based on the criteria of spatial proximity and distance to the plane. The time complexity (nlogn) can be considered as one of the strong sides of the algorithm to work with large volume of dataset. Since distance to the plane is only a criterion to add points to the growing plane, this may not give good results towards the sharp edges. There will always be a tendency of accepting the points that belongs actually to other segment, which falls within the thickness generated by distance to the growing plane. Tóvári and Pfeifer (2005) use local surface normal as an additional criterion during the plane growing. It is noteworthy to mention that the seed plane selection strategy used by Tóvári and Pfeifer (2005) is different than the one used by Vosselman et al. (2004). The comparison of local surface normal is not necessary for planar surface detection towards the interiors of the surface where distance to the plane is sufficient criteria. This adds additional computational complexity to the algorithm if we compute local surface normal to each point in the point cloud and verify the local surface normal similarity. On the other hand, local surface normal computed should itself be accurate, which is hardly achieved for

points towards the sharp edges and for noisy point clouds. This demands separate strategy to correctly assign segment number to the points towards the edges.

Based on the above mentioned observations, the segmentation strategy suggested by Vosselman et al. (2004) is adapted to our problem of segmenting coloured point clouds data. The main steps are described in details on subsequent sub-sections.

3.5.1. Data structure

In unstructured point clouds, we do not have any explicit connectivity information between points. One of the commonly adopted approaches in dealing with point clouds is based on spatial proximity of points. Before starting main process of segmentation, development of suitable data structure is important to improve neighbouring points searching efficiency. The data structuring method provides the explicit neighbourhood relation to each point e.g. indices of points that are adjacent to any given point. By using a suitable data structure like k-d tree, the neighbourhood searching can be optimized (Rabbani et al., 2006). This k-d tree can be used to create adjacency information of points by maintaining a list of the indices of k-nearest neighbours to each point. The adjacency of points defined by k-nearest neighbours has some desirable properties (Rabbani et al., 2006) in working with unstructured point clouds. Since number of neighbouring points (k) is fixed, area of interest varies according to the point density. This implies that the neighbouring list prepared using the indices of k-nearest neighbours are adaptive to the local point density of point clouds. These are illustrated in Figure 3-2. Rabbani et al. (2006) further mentions that this method always uses the given number of points that ensures every point having neighbours.

(a) (b)

Figure 3-2: Adaptation of radius for k-neighbours (a) Larger radius for low density and (b) Smaller radius for higher density data

3.5.2. Use of colour space

The use of colour metric depends upon the colour space employed which itself depends on the colour information available. As the RGB colour space has some limitation in colour similarity representation, the HSI and CIEL*a*b* spaces have some desirable properties. As mentioned in section 2.5.1, the HSI space resembles the human perception of colour information. One of the difficulties in using HSI space is its cyclic nature, which could be handled employing appropriate algebra. However, the use of HSI space suffers from yet another limitation. In low saturation or

intensities, hue information becomes numerically unstable while intensity becomes dominant in colour metric. As CIEL*a*b*colour space is a uniform space, colour differences can directly be measured using the Euclidean distance. This motivated us to use CIEL*a*b*colour space as suitable colour space. Since the colour similarity measurement metric directly depends on the employed colour space, the colour metrics defined in the proposed algorithm is based on CIEL*a*b*colour space. To measure colour similarity using HSI colour space in the same algorithmic structure, the colour metric should be changed accordingly.

The use of CIEL*a*b*colour space demands different strategies to reduce the effect of illumination variation and shadow. The illumination variation can be taken into account by comparing colour information only at local region. The important assumption behind this is that the illumination level at local region is uniform. The effect of strong shadow is adverse on the result of segmentation process as it tends to create over-segmentation of the planar surfaces. The effectiveness of currently chosen colour space in minimizing the effect of shadow on segmentation is unknown at this stage. If the effect remains adverse, this can be considered as possible limitation of the currently chosen colour space.

3.5.3. Seed plane selection

Selection of seed plane is crucial in region growing approach of segmentation since this seed plane is later grown towards the neighbourhood of points. As explained in section 2.3.2, to detect a plane in a local neighbourhood of any arbitrarily selected seed point, first, neighbouring points around it are estimated and the points are tested whether they fit on a plane or not. If there are sufficient number of points i.e. larger than certain threshold, which fit well on a plane in local neighbourhood and meets colour similarity criteria, then the detected plane can be accepted as seed plane. The important question remains, though, is *"how to define local neighbourhood and estimate points that belongs to the defined neighbourhood?"*

One of the commonly used approaches to define local neighbourhood in unstructured 3D point clouds is to use spherical neighbourhood centred on the seed point. All the points that are within a certain distance from the seed point are considered as adjacent points. Generally, this distance is defined as radius threshold value. Extracting points that falls inside a sphere of certain radius is crucial as it dictates the computation time of the algorithm. Another approach is to use k-neighbours (Rabbani et al., 2006) to seed point. This approach is computationally efficient as there is no need to search points within certain distance threshold value on the data structure defined above in section 3.5.1. One of the drawbacks, however, is that there may be tendency of detecting plane in sparsely distributed points as it adapts the area of interest according to the point density. This situation can be avoided using radius threshold value. Considering only the points that are within certain radius (r_{ths}) and are of k-neighbours, the computational efficiency can be achieved and avoids the inclusion of distant points as neighbours as well.

Once neighbouring points are estimated, these can be used to detect seed plane. For this purpose, robust least square adjustment of plane or 3D Hough transforms (Vosselman et al., 2004) or RANSAC can be used to detect planes in the presence of outliers. For implementation purpose in this

research, Hough transform using normal form of plane equation is considered because of the availability of class library.

If a plane is detected, plane parameters should be recomputed using all the points whose distance is lesser than the specified threshold (d_{ths}) to the detected plane. After computation of plane parameters, number of points that fall within the thickness of plane specified by maximum distance of a point to the plane threshold value (d_{ths}) are counted. If this number is greater than minimum number of points (n), following criteria are tested while determining whether or not to accept detected plane as seed plane. The detected plane is accepted only if all the criteria are satisfied.

To accept detected plane as seed plane, following criteria are set:

1. Geometrical criteria:
   This verifies that the distance of a seed point to the plane (d) is below input threshold i.e. $d < d_{ths}$

2. Colour similarity:
   As the geometrical and colour information are treated separately as mentioned in section 3.3, the colour similarity of the plane is suggested to test only if it satisfies the above geometrical criteria. The idea behind this is to avoid outlier points in colour similarity measurement. For colour similarity, the criteria are:
   i. Colour distance ($\wp$) of seed point to the points in detected plane is below the input threshold ($\wp_{ths}$) and
   ii. Colour variance of the points in detected plane (v_T) is below some threshold (v_{th}).

   This can be expressed as:

   Colour similarity = $\begin{cases} true, if\ \wp < \wp_{ths} \quad and \quad v_T < v_{th} \\ false, Otherwise \end{cases}$

The colour distance ($\wp$) is computed using equation (2.10) which is the distance of a colour to the mean colour of a region. If colour distance threshold value is known, the maximum allowable variance of a region (v_{th}) can be considered as the square of the distance threshold and is computed as:

$$v_{th} = \wp_{ths} * \wp_{ths} \tag{3.4}$$

The variance (v_T) is computed using the relation given below:

$$v_T = v_{11} + v_{22} + v_{33} \tag{3.5}$$

The values v_{11}, v_{22} and v_{33} are computed using equation (2.12) for each colour channel.

Here, variance of a region should be considered along with the colour distance criteria. This consideration is important to avoid the detection of seed plane especially towards the colour edge. If

seed plane is near or at the boundary of a region, variance criterion avoids the detection of seed plane there.

Once acceptable seed plane is detected, the region growing process starts which is described in details on subsequent sub-section.

3.5.4. Plane growing

After detecting a seed plane, the points belonging to seed plane are transferred to the growing region and the plane equation is initialized as a growing plane equation. All the points in growing region are iterated and neighbouring points are added to the region if similarity criteria satisfy. During the plane growing, one point is considered at a time to test whether it belongs to the same region of growing plane or not. The growing of plane is stopped if no more points can be added to the plane. Once growing of plane is stopped, another point not yet assigned to any region is selected as next seed point and the same process repeats afterward.

To enforce the spatial proximity of points, the similar neighbourhood definition as explained in seed plane selection is used. The radius used to grow plane has crucial role as small value may lead to the creation of fragmented segments. This situation is obvious in the presence of outliers and varying density dataset. On the other hand, large value may cause the growing plane to cross a plane and jump into another one. This is elaborated in the subsequent paragraph.

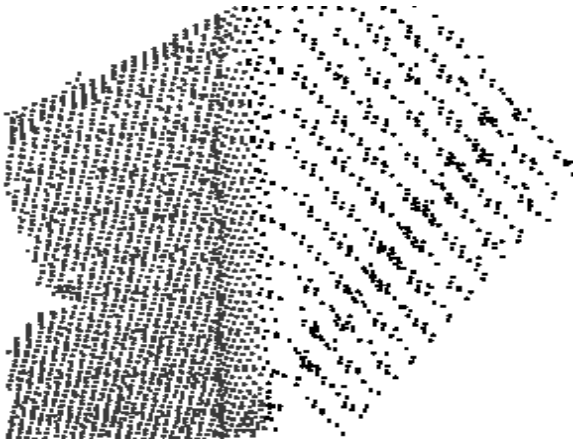
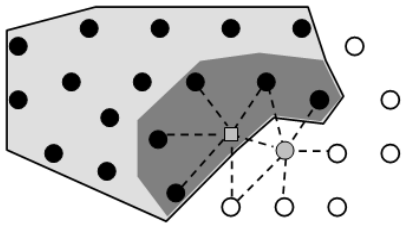


Figure 3-3: Laser points with different point density

The Figure 3-3 represents parts of roof segments having different point density in two adjacent roof parts. In such a case, if radius of neighbourhood is not chosen carefully, the roof segment on right side may end up with many striped segments.

During plane growing also, both geometrical and colorimetric criteria are tested separately for each candidate point. Before presenting these criteria, description of some terminologies used in its definition is provided. These include global region, local region, region point and candidate point. These are shown in Figure 3-4 with their descriptions.



: Global region, considers all the points in currently growing plane.

: Local region, considers only those points which are in growing plane and within the neighbourhood of both region point and candidate point.

: Region point, a point in global region which is used to grow the region towards its neighbourhood

: Candidate point, a point which is under testing and is within neighbourhood of region point.

: Line showing points in neighbourhood.

Figure 3-4: Global and Local regions

To accept a candidate point to the growing plane, following criteria are set:

1. Geometrical criteria:
   It is accepted only if the distance of candidate point to the growing plane is below input threshold i.e. $d < d_{thg}$

2. Colour similarity:
   For colour similarity, following criteria are used:
   i. Colour distance ($\wp 1$) of candidate point to the points in local region inside growing plane is below the input threshold ($\wp_{thl}$) and
   ii. Colour distance ($\wp 2$) of candidate point to the points in growing plane (here taken as global region) is below the input threshold ($\wp_{thg}$)

This can be expressed as:

$$\text{Colour similarity} = \begin{cases} true, & if\ \wp 1 < \wp_{thl} \quad and \quad \wp 2 < \wp_{thg} \\ false, & Otherwise \end{cases}$$

In the criteria (2), the colour mean of local region is computed using points adjacent to both region point and candidate point, which are already in growing segment. The consideration of local region enables to verify colour homogeneity on local region. The main assumption made here is that colour at local region is homogeneous. Here, consideration of local region for colour homogeneity measurement is important to allow growing of region even in the presence of colour variation. The same radius used to grow seed can also be used to estimate the local points while computing colour similarity.

The criterion of colour distance to local region is not sufficient during plane growing. This criterion may fail if there is smooth transition between two colour regions. In such a case, the smooth transition region allows to grow a plane towards the different colour region. To handle such a case, a threshold value measuring the distance of candidate point to the mean of global region can be used. This threshold ($\wp_{thg}$) is suggested to keep relatively larger than the distance to local region threshold ($\wp_{thl}$).

Consideration of edges

As certain thickness around growing plane is used to accommodate the noise or surface roughness by imposing a distance to plane threshold, this may cause taking the points in the edges that belong actually to other plane. This is illustrated in Figure 3-5 below, which is assumed to be a part of the two wall segments where points in one wall are assigned a segment number to that of its adjacent wall segment.

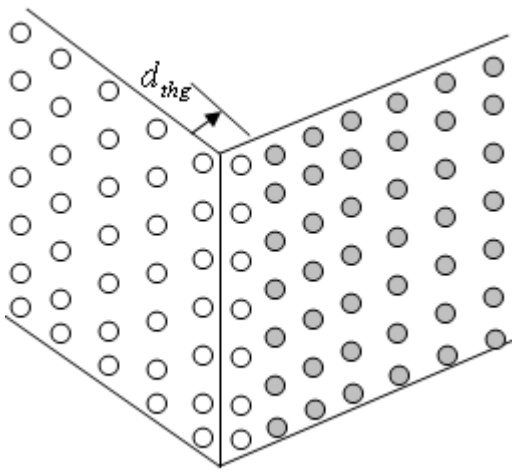


Figure 3-5: Erroneous edge segments where points that belong to one segment are assigned a segment number of adjacent segment

To deal with this problem, the local surface normals can be computed for each point and the similarity of local surface normal of candidate point to the normal of growing plane can be tested as an another criterion in addition to the distance to plane. To avoid the computation of local surface normal, alternative approach is used in this research. In such cases, for each edge point, the distances to both planes are computed and the segment number of a point is reassigned to that of the closest segment if colour similarity criteria also satisfy.

This consideration of edge points can be integrated into the region growing phase. If neighbouring point under testing has already been assigned different segment number than that of the current

growing plane, then an angle between two planes is computed. If the angle is greater than certain value, two segments are considered as edge segments. The closeness of distance to both planes are tested and the segment number is changed to current segment number if the distance to current plane is smaller after verifying colour similarity criteria. This ensures that the edge points are correctly assigned to the respective segments and avoids the computation of local surface normals. To reduce the effect of surface roughness, root mean square of distances of the points (in the neighbourhood of a candidate point) to the respective segments are computed. The candidate point is assigned to the currently growing segment if root mean square of distance to the current segment is lesser than other.

Towards the colour edges, the effect of mixed pixels may cause the edge points not to be assigned to either segment. These points are later processed separately to add in the closest segment if similarity criteria satisfy. To allow certain level of noise, only distance of a candidate point to the adjacent point in segment is computed.

Adjustment of plane parameters

After adding each point in the plane, parameters are needed to be re-computed. But adjustment of the plane parameters after adding every point cost computational time. Therefore, the plane parameters are adjusted in certain intervals after adding certain number of new points. The eigenvector/ eigenvalue approach using the moments of the point coordinates is applied for the plane parameter adjustment.

3.6. Outline of algorithm

Based on the description of the various aspects of proposed algorithm, a summary is presented in Table 3-1. Before outlining the summary of algorithm, the input parameters are provided. These parameters can be used as the threshold values. These include:

k = number of nearest neighbours to each point

n = minimum number of points in seed plane

r_{ths} = neighbourhood radius for seed selection

d_{ths} = maximum distance of point to the seed plane

$\wp_{ths}$ = maximum colour distance of a point to the mean of the points in seed region

r_{thg} = neighbourhood radius for growing of plane

d_{thg} = maximum distance of point to the growing plane

$\wp_{thl}$ = maximum colour distance of a point to the mean of the points in local region

$\wp_{thg}$ = maximum colour distance of a point to the mean of the points in global region

In addition, parameters used for Hough transform are:

d_b = bin size for distance

a_b = bin size for angle

Table 3-1: Outline of proposed algorithm

Step 1:	Prepare k-nearest neighbours list utilising k-d tree data structure
Step 2:	Transform colour to the chosen colour space

Step 3:
 	
Seed Plane Selection
	• Remove label of all points in point clouds
	For each unlabelled point (i.e. seed point) in point clouds
	• find neighbouring points
	• detect plane in neighbouring points (Hough transform)
	• compute plane parameters
	• count number of points that are within d_{ths} distance from the plane
	If number of points in plane > n then
	• calculate distance of seed point to detected plane
	• set geometrical similarity flag as true if distance < d_{ths}
	End if
	If geometrical similarity flag is true then
	• compute the colour mean and colour variance using points in detected plane
	• calculate colour metric of seed point to the detected plane points
	• compute colour similarity measure of detected plane
	If similarity criteria satisfies then
	• seed plane is found
	• label all points in detected plane as new plane
	• proceed for plane growing
	End if
	End if

Step 4:
 	
Plane Growing
	• set the seed plane as growing plane
	• set the colour mean of seed plane as current colour mean
	For each region point in the growing plane
	• find the neighbourhood of points
	For each candidate point in the neighbourhood of points
	• calculate distance to growing plane
	If candidate point is unlabelled then
	• set geometrical similarity flag as true if distance < d_{thg}
	Else if candidate point is labelled other than current plane
	• check for edge point and calculate closeness to both planes
	• set geometrical similarity flag as true if candidate point is closer to current plane and distance < d_{thg}
	End if
	If geometrical similarity flag is true then
	• find points in local region
	• calculate colour metric to local and global region
	• compute colour similarity measure of candidate point
	If colour similarity criteria satisfies then

- add candidate point to growing plane i.e. Label the candidate point as the current label
- update colour mean
- update plane parameters

Else

- collect point in eligible point list

End if

End if

End for

End for

End for

For each unlabelled point (eligible point) in eligible point list

- find neighbouring points that are labelled
- find point in neighbourhood for which distance of eligible point to the plane of neighbouring point is under threshold ($< d_{thg}$) and is the smallest colour distance as compared to other neighbouring point
- label the eligible point as the same label of above neighbouring point.

End for

3.7. Concluding remarks

In this chapter, the approaches used to create coloured points clouds are presented. Thereafter, possible segmentation strategies are discussed. An algorithm based on single step segmentation strategy is further development in which geometrical information is considered as first order information. To reduce the effect of fine details and noise in colour information, a pre-processing step is introduced. This includes the extension of vector median filter to work with point cloud data.

A four step algorithm based on region growing approach is proposed. First, k-d tree data structure is utilized to create a list of k-nearest neighbours to each point, then RGB colour is transformed into CIEL*a*b* colour space. The algorithm is structured in such a way that other colour spaces can also be used provided that the colour metric is changed appropriately. Finally, region growing based approach starts which basically has seed plane selection and plane growing steps. Information of global region is utilized to test geometrical similarity. To minimize the effect of colour variation, points in local region are used in colour similarity measurement. Finally, an outline of the algorithm is presented to aid the implementation task. The implementation of the algorithm is described in next chapter.

4. Implementation and Results

4.1. Introduction

Implementation of the developed algorithm as computer codes is necessary to test the algorithm. This chapter focuses on the implementation of the algorithm designed in previous chapter. First, different datasets are described in section 4.2. Before going to segmentation, results from the pre-processing of colour is presented in section 4.3. The results produced by processing of the data are presented in section 4.4. The quantitative analyses of the results are presented in next chapter.

4.2. Datasets

Nowadays, unstructured 3D coloured point clouds are captured from both terrestrial and airborne laser scanning systems; it is worthy to test the algorithm on both datasets. For this purpose, separate datasets acquired from both air borne laser scanning (ALS) and terrestrial laser scanning (TLS) systems are used. The details about the data and their characteristics are described in the subsequent paragraphs.

Vlaardingen data (TLS)

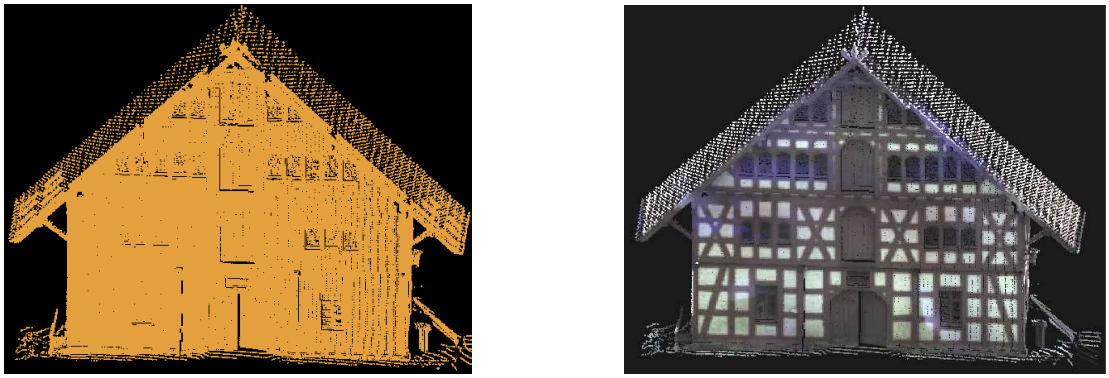
This data contains three connected buildings from Vlaardingen area, Netherlands and was captured from terrestrial laser scanning system. It includes façade elements such as walls, doors, windows, roofs and dormers. The colour is captured from the inbuilt camera of Leica scanner. The point density of the data is not uniform. Figure 4-1 shows the visualized data. The colour is not uniform on the same surface; for example on the wall or on the roof.

(a) (b)

Figure 4-1: Vlaardingen data coloured based on (a) fixed value and (b) RGB value

German building data (TLS)

This data is an old farm house at Sankt Johann, Germany and obtained from the website of University of Stuttgart, Institute of Photogrammetry. This data was acquired with Leica HDS3000 and used by the author of Böhm and Becker (2007) for registration of laser scans. The author mentions that the data was acquired with average point spacing of 2cm on the object surface. The colour information is from the inbuilt camera. This data typically has repetitive features of window and beams in wall. Figure 4-2 is the visualization of this data.

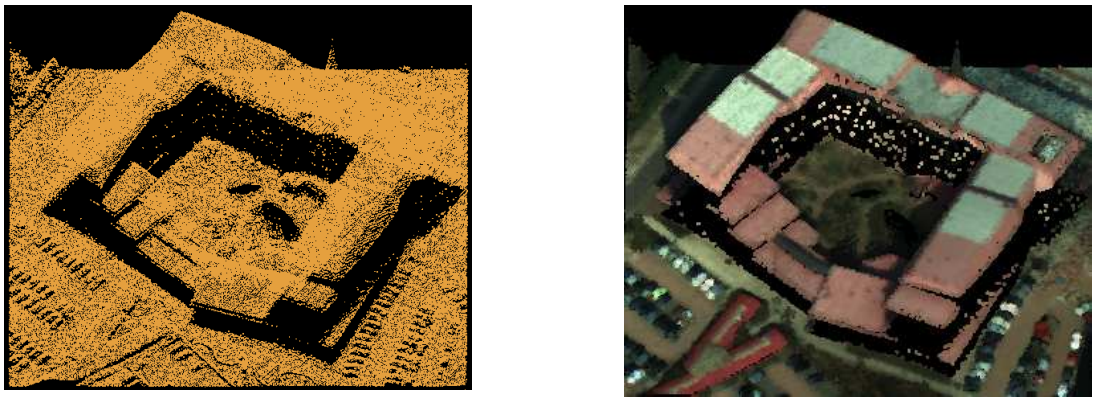


(a) (b)

Figure 4-2: German building data coloured based on (a) fixed value and (b) RGB value

ITC building data (ALS)

This data was captured from the airborne laser scanning system. This data is acquired by FLI-MAP 400 system. The average point density of data is 10points/m^2. This typically has roof elements of ITC building. Some parts of the roofs are covered by shadow.

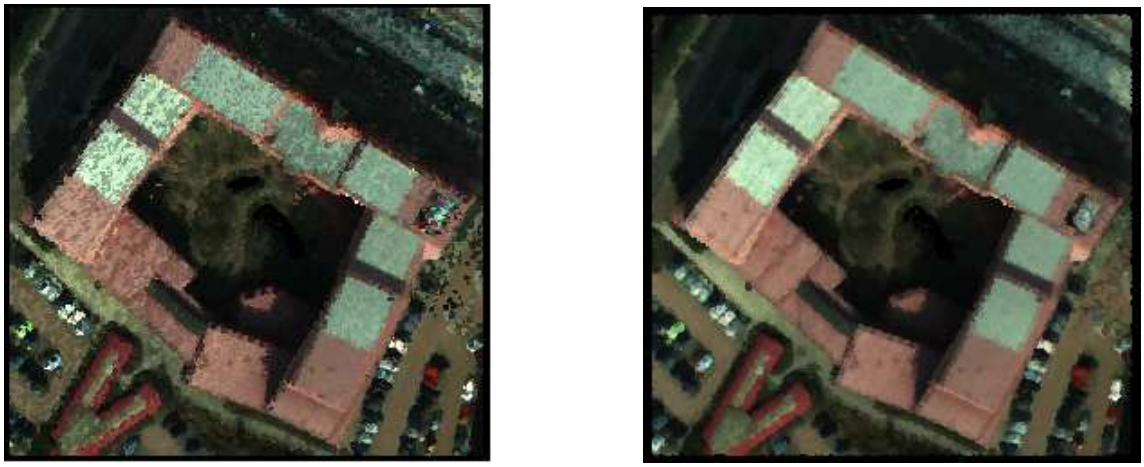


(a) (b)

Figure 4-3: ITC building data coloured based on (a) fixed value and (b) RGB value

4.3. Pre-processing

All the datasets are processed with vector median filter (section 3.4) on RGB colour space as pre-processing step. The values of k-nearest neighbours are chosen empirically by examining the results. Typically, 10 neighbours are used for TLS data and 5 neighbours for ALS data. Figure 4-4 shows the point clouds before and after applying vector median filter as an example. The small details are removed while applying the filter. These datasets are further used for segmentation.



(a) (b)

Figure 4-4: Coloured point clouds of ITC building (a) before applying filter and (b) after applying filter

4.4. Data processing

The developed algorithm is tested with various datasets described in section 4.2. Parameter optimization is carried out for all datasets to get the optimal results. The following parameters are required as input.

a) Number of nearest neighbours
b) Hough transform
    - Size of bin for distance
    - Size of bin for angle
c) Seed plane selection
    - Minimum number of points in seed plane
    - Seed neighbourhood radius
    - Distance to plane
    - Colour distance
d) Plane growing
    - Neighbourhood radius
    - Distance to plane
    - Colour distance for local region
    - Colour distance for global region

The following sub-section describes the method of tuning parameters to obtain optimal results.

4.4.1. Parameter selection

As the developed algorithm requires several input parameters to define thresholds, the tuning of parameters for different dataset is important to get the best result. In Hoover et al. (1996), parameters for different algorithms are selected by defining the range of values to each parameter and exploring all the possible combination of them. However, approximate values are chosen by the visual

examination of the intermediate results. In our work, different parameters are optimized based on various trials and visual evaluation of the segmentation results.

The number of nearest neighbours is one of the key parameters, which helps to optimise neighbourhood search operation. This parameter is set higher than minimum number of points required to accept detected plane as seed plane. As k-neighbours within certain distance are considered as neighbouring points, outliers as well as distribution of points should be taken into account. Another consideration is that k-nearest neighbours may not necessarily contain all the points that falls within the sphere of certain radius. By using relatively larger k-neighbours, there will be increased possibility of taking more points into consideration with the same radius value. By examining the datasets and observing the distribution of points, this value is set for different dataset as given in Table 4-1.

Table 4-1: k-nearest neighbours

Dataset	k-nearest neighbours
Vlaardingen data	20
German Building data	20
ITC Building data	20

The minimum number of points required to accept a detected plane in seed plane selection depends on the point density of the dataset and the minimum size of desired object surfaces. The minimum size of object surface that can be extracted from the given data is dependent to the point density. The values set for different dataset are given in Table 4-2. These values are chosen after examining the dataset and observing the number of points present in the objects.

Table 4-2: Minimum number of points in seed plane

Dataset	Minimum number of seed points
Vlaardingen data	10
German Building data	10
ITC Building data	8

The neighbourhood radius for seed plane selection and plane growing directly depends on the minimum points required to detect the seed plane and the point spacing of data. As k-nearest neighbours are used here, this adapts the local point density around a point to create neighbourhood list of that point. Since this information is exploited during the algorithm design, the radius of neighbourhood for seed plane selection is set so as to avoid the distant points and selecting seed on sparsely distributed region. The optimal radii are given in Table 4-3. These values are selected after following the performance evaluation of algorithm and based on the result presented in Table 5-9.

Table 4-3: Neighbourhood radius in meters

Dataset	Neighbourhood radius (m)	
	Seed selection	Plane growing
Vlaardingen data	0.15	0.20
German Building data	0.25	0.25
ITC Building data	1.5	1.75

Distance to plane is one of the key parameters dictating the output of the algorithm. When this parameter is kept low, planar objects having rough surface are segmented into many planes, for example, roof having tiles will be segmented into many segments. On the other hand, when kept higher, planes will not be detected as desired. This parameter is selected after many trials with subjective judgement of the result. This value typically does not depend on the point spacing of the dataset. This indeed also depends on the point accuracy of laser scanning i.e. different for terrestrial and airborne laser scanning systems. The parameter values for seed plane selection and plane growing are given in Table 4-4.

Table 4-4: Distance to plane in meters

Dataset	Distance to plane (m)	
	Seed selection	Plane growing
Vlaardingen data	0.08	0.08
German Building data	0.08	0.08
ITC Building data	0.20	0.25

The colour distance is also set by evaluating many trials. The colour distance for seed selection and the colour distance to local region during growing have similar values. The colour distance to global region is kept higher than that of the local region. These parameter values are given in Table 4-5.

Table 4-5: Colour distances

Dataset	Colour distance		
	Seed selection	Local region	Global region
Vlaardingen data	8	8	20
German Building data	8	8	20
ITC Building data	10	10	15

In addition, the size of bin for distance is set to 0.1m and size of bin for angle is set to 3 degree for all the datasets. These values are also derived empirically. The results after processing of data are presented in subsequent sub-section.

4.4.2. Results

Based on the various parameters setting, the results of processed data is presented from Figure 4-5 to Figure 4-7. It is observed from the results that the segmentation algorithm is able to generate appropriate segments. In general, majority of bigger segments are detected appropriately. Still, there are some irrelevant segments generated on the interiors of the larger segments as well as towards the edges. More detailed observations based on the visual examination of the result for each data are described below.

The observation of the result presented in Figure 4-5 shows that the algorithm is able to detect all the orientation of planar surfaces present in the data. Furthermore, larger surfaces (e.g. walls, roofs) as well as smaller surfaces (e.g. parts of dormers, windows frames) are extracted. It can be observed that there are many small segments near the ground. This is obvious that presence of other objects like cars has lead to produce such segments. Another observation is that although the window frames are

separated from the wall segments, they are represented by more than one segment. This is because of the fact that colour is not uniform in all the points of single window frame. The small segments on the interiors of larger segments or towards the edges are observed which is basically caused by colour variation.

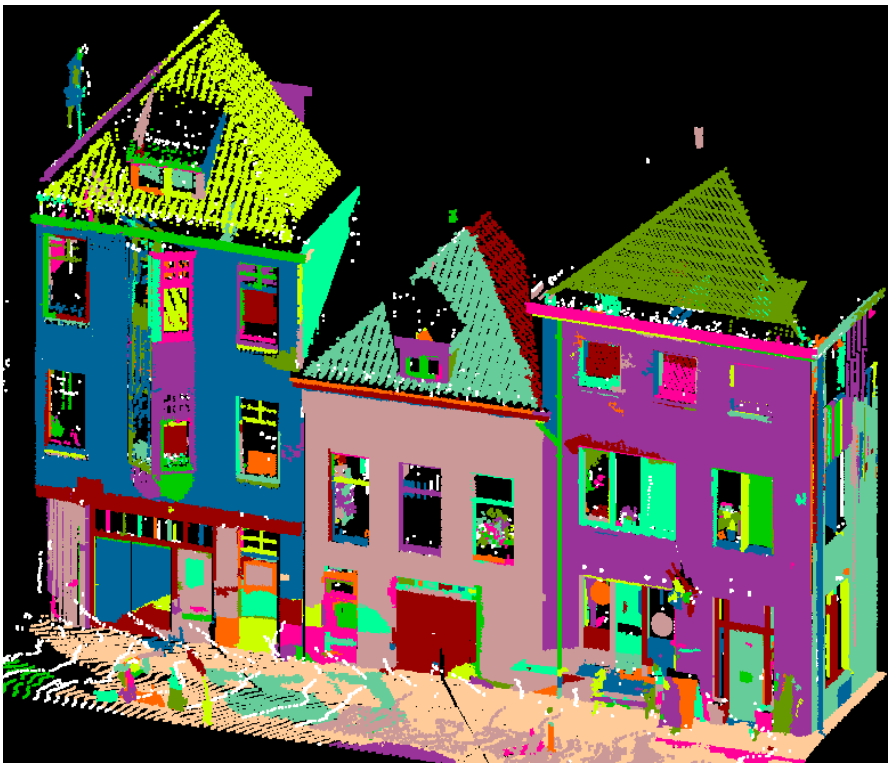


Figure 4-5: Segmented point clouds of Vlaardingen data

Figure 4-6: Segmented point clouds of German building

The first observation on the result of German building data (Figure 4-6) shows that most of the planar areas are separated creating patterned wall as seen in the coloured point cloud. The most important thing is that the regions with different shapes and sizes are properly extracted. However, in some portion the effect of colour variation is clearly noticeable, which could be due to the noise in the colour.

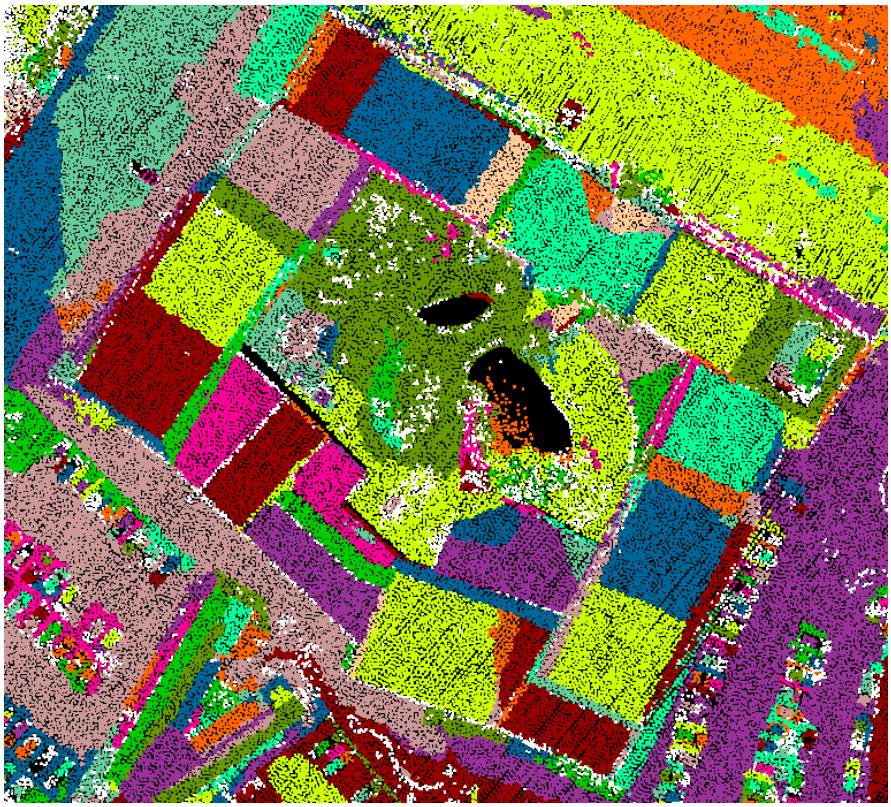


Figure 4-7: Segmented point clouds of ITC building

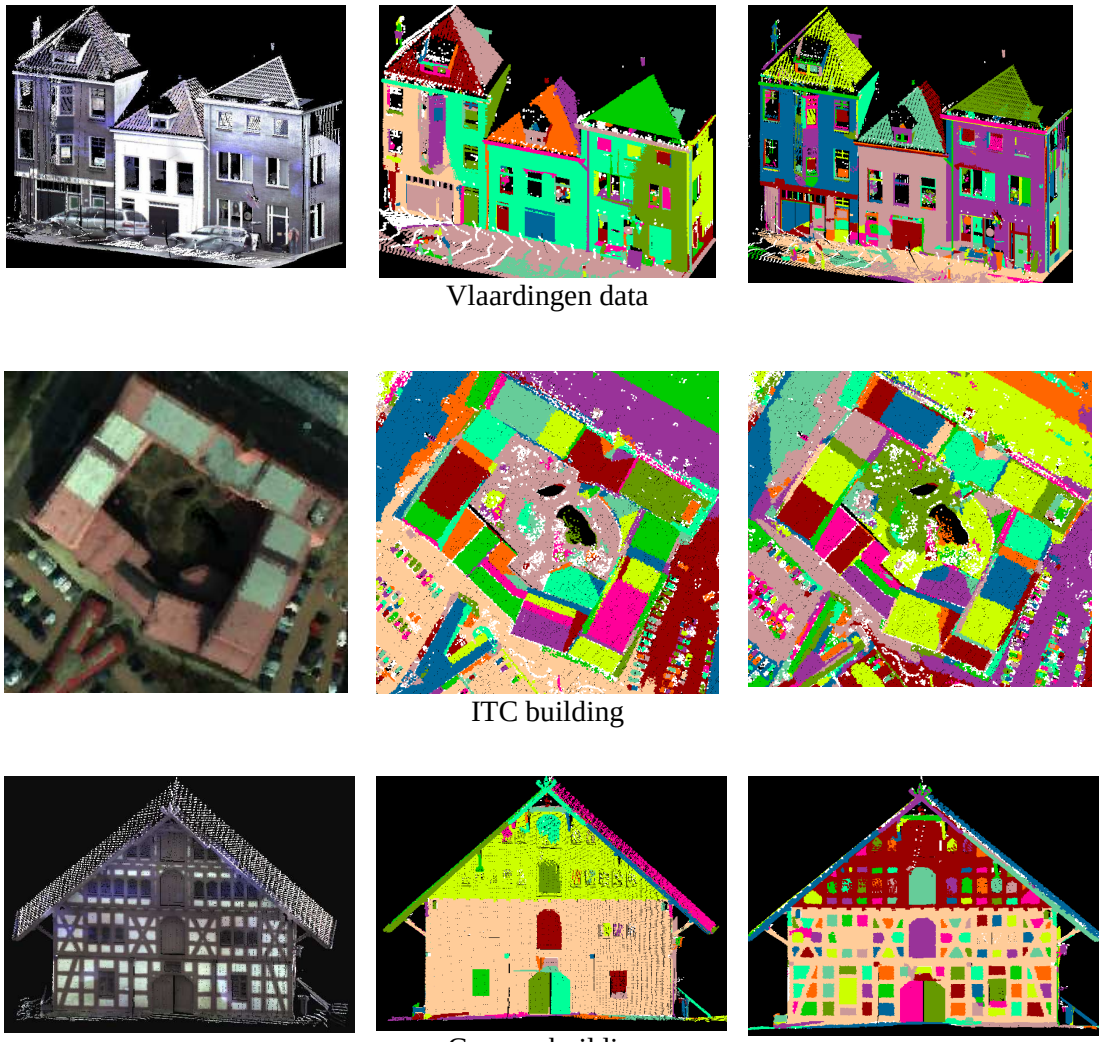
The result (Figure 4-7) reveals that all the roof segments are created and roof sections that contain different colour are separated appropriately. The effect of shadow is noticeable in the result due to which some shadowed roofs are segmented into more than one region. It is also observed that there are some thin elongated segments towards the edges. Furthermore some roof sections are separated into more than one segment. The reason behind this could be due to non-conformance of the roof to the planar geometry even though it has similar colour.

4.5. Segmentation without using colour

To explore the benefit and limitation of colour information in segmentation process, same datasets are segmented with geometrical information only and subjective comparisons are made. For this, the colour similarity criteria are turned off and other parameters are set same as in the previous processing. The results are presented in Figure 4-8 together with coloured point clouds and segmentation results with utilising colour information.

While comparing the coloured point clouds with the segmentation results processed with only geometrical information, we can observe some irrelevant segmentation results. The walls of three

buildings are combined in one segment; wall segment is also including the points from window (Figure 4-8, top row) which has different colour. The segmentation result does not reveal any information about the colour variation of roof (Figure 4-8, middle row) or wall (Figure 4-8, bottom row). If regions of different colour are considered separate parts of building, direct use of this result would create difficulty in accurate modelling of building geometry.



(a) (b) (c)

Figure 4-8: Comparison of segmentation results (a) RGB colour (b) segmentation without colour (c) segmentation with colour

Based on the observation of results, use of colour information is able to produce segments that are not possible by using only geometrical information. For example, wall of middle building is separated from adjacent buildings and window frames are separated from wall segments in Vlaardingen data. Similarly, regions with different colour than its surroundings are segmented on ITC as well as German building data.

The use of colour information has shown some limitations in segmentation. Especially for Vlaardingen data, many undesired small segments are created near the ground while using colour. This is because of the presence of additional objects e.g. cars. Another important observation is that

additional segments are generated by the presence of strong shadows as well as the colour variations if we use colour. Some effects can also been seen towards the edges because of the colour variation.

4.6. Concluding remarks

In this chapter, the algorithm proposed in chapter 3 is implemented and tested with different datasets. Two datasets acquired from terrestrial laser scanning and one from airborne laser scanning systems are used as test datasets. To remove small details and noise present in colour information, the point clouds are pre-processed with vector median filter. Then these datasets are processed using optimised parameters and the results are presented.

Based on the observation of the results, it can be concluded that the use of colour information in segmentation process is able to detect surfaces which are not possible only by using geometrical information. The algorithm is able to extract large segments such as walls/roofs as well as small segments such as surface on dormers. The algorithm is able to minimize the effect of colour variation on the surfaces. In the mean time, the observations on results show that colour tends to produce some irrelevant segments. The effect of shadow is adverse in the segmentation result. More detailed quantitative evaluation of the result is presented in next chapter.

5. Performance Evaluation

5.1. Introduction

After processing of data with the best set of parameters, quantification of quality of the obtained results is important to assess the performance of the developed algorithm. At the same time, it is equally important to see the behaviour of the algorithm with changing parameters. This chapter defines the performance measurement framework in section 5.2; then description about the preparation of data for evaluation task is provided; finally analyses of various results are presented in section 5.5.

5.2. Performance measurement framework

The performance measurement of any segmentation algorithm is conducted by analysing the resulted segments by that algorithm. This task requires truth data or reference data against which the resulted segments can be compared. The algorithm is expected to produce results matching the reference dataset. In the ideal case, segmentation procedure outputs exactly the same segments as in the reference data. However, the ideal case can hardly be achieved as the real dataset always contains various noises and exact borderline of segment can not be found. Thus, it requires a framework for quantitative evaluation of the results.

Hoover et al (1996) provides methodology to evaluate the result of segmentation, originally designed for range images. Similar framework is adopted by Geibel and Stilla (2000) for the comparison of different procedures in segmentation of laser altimeter data. These methods are basically designed to work with raster based segmentation. Nyaruhuma (2007) adopts the similar technique for the performance evaluation of different algorithm in detecting roof faces from 3D point clouds. The underlying principle is based on the comparison of the resulted segments with the corresponding reference segments and evaluation of matching of points belonging to both surfaces. To measure the correspondence between these two datasets, common points that belong to both datasets are taken into account. The correspondence measurement includes the task of creating intersection matrix to evaluate various metrics.

Let S_r be the segment in reference data and S_o be the output of the segmentation algorithm. To measure the correspondence between these two segments, the number of intersection points is taken into account. An intersection matrix is prepared where columns are represented by the segments in reference data and rows are represented by the segments in the output of the segmentation process. Each element of matrix is filled by the number representing the number of intersecting points (i.e. common points) between two corresponding segments. The various metrics are quantified as:

Correct segmentation

A segment is considered as correctly detected segment if majority of points in reference segment are also labelled as a single segment in the result. The majority percentage is defined by the tolerance value and 50% is taken as minimum value. This can be expressed as:

$$M_r = \frac{N_{ro}}{N_r} \text{ and } M_o = \frac{N_{ro}}{N_o} \tag{5.1}$$

Here, two measures M_r and M_o are the ratio of intersection points (N_{ro}) to the total number of points in reference segment (N_r) and output of the segmentation algorithm (N_o) respectively. A pair of segments in reference data and segmentation result are classified as an instance of correctly detected segment if both measures are greater than certain tolerance value (T) and is expressed as:

$$M_r > T \text{ and } M_o > T \tag{5.2}$$

Over-segmentation

This is the case where one segment in reference data (S_r) is represented by more than one segments ($S_{o1} + S_{o2} + ...$) in output of the algorithm. In this case, the total number of intersection points is the sum of intersection points in many S_o segments i.e. $N_{ro1} + N_{ro2} + ...$.

$$M_{ro} = \frac{N_{ro1} + N_{ro2} + ...}{N_r} \text{ and } M_{oo} = \frac{N_{ro1} + N_{ro2} + ...}{N_{o1} + N_{o2} + ...} \tag{5.3}$$

Here, $N_{o1}, N_{o2}, ...$ corresponds to the total number of points in segments $S_{o1}, S_{o2}, ...$ respectively.

If these two measures are greater than certain threshold value T, reference segment S_r can be classified as an instance of over-segmentation. However, if more than one S_o-segments intersect with a S_r-segment, there may be one S_o segment already classified as an instance of correctly detected segment. In that case, averages of the two measures are compared and the classification is assigned as over-segmentation only if equation (5.4) holds.

$$\frac{M_{ro} + M_{oo}}{2} > \frac{M_r + M_o}{2} \tag{5.4}$$

Under-segmentation

If one segment (S_o) in the output of the segmentation process intersects with more than one reference segments ($S_{r1} + S_{r2} + ...$), this causes the instances of under-segmentation. This can be considered as the case of insufficient separation of multiple planar surfaces. Likewise in over-segmentation, the total number of intersection points is the sum of the intersection points in many S_r segments i.e. $N_{r1o} + N_{r2o} + ...$.

$$M_{ru} = \frac{N_{r1o} + N_{r2o} + ...}{N_{r1} + N_{r2} + ...} \text{ and } M_{ou} = \frac{N_{r1o} + N_{r2o} + ...}{N_o} \tag{5.5}$$

The values of $N_{r1}, N_{r2}, ...$ are the total number of points in segments $S_{r1}, S_{r2}, ...$ respectively. If these two measures are greater than certain threshold value T, reference segments ($S_{r1}, S_{r2}, ...$) can be classified as an instance of under-segmentation. But if one S_o-segment intersects with many S_r-segments, one of the S_r-segments could already be classified as correct or over-segmentation. In such case, averages of the current measures and the measures of former classification are compared and the classification is assigned as under-segmentation only if current measure is greater than the previous one as in the case of over-segmentation.

Missed segment

A reference segment (S_r) is classified as missed segment if this does not participate in any one of the instances of correct, over and under-segmentation.

Noise segment

A segment (S_o) in the output of the segmentation process is classified as noisy segment if the segment is classified neither as an instance of correct segmentation, nor as of over-segmentation, nor as of under-segmentation.

Geometrical accuracy

In addition to the classification of the segmentation results described above, the geometrical accuracy of the extracted segments is estimated. In Hoover et al. (1996), the angle between any two adjacent segments are computed only for the accurately classified segments. The difference in angle of two faces in reference data and the angle of their corresponding faces in segmentation results are computed and the average errors as well as the standard deviations of the angles are reported to quantify the accuracy of the detected segments. However, Nyaruhuma (2007) argues that the angle between adjacent segments can not always be compared. This demands the independent comparison of plane parameters of a segment in reference data with corresponding segment in the result. In general, some error tolerance (i.e. distance of a point to its plane) is accepted while adding points in a segment; this may lead to the different set of plane parameters of a detected segment than that of the corresponding segment in reference data. The angle between the surface normals of two planes can quantify the geometrical accuracy of the segments. This approach is used by Nyaruhuma (2007) where root mean square errors (RMSE) of angles between reference planes and planes of the corresponding result segments are computed to assess the accuracy.

Based on the framework described above, a tool is prepared to quantify the performance of the developed algorithm. This tool takes reference dataset and the segmentation results as input and produces the report of the number of correctly detected segment, over, under, noisy and missed segments along with the angle error for each preset tolerances e.g. 0.51, 0.6, 0.7, 0.8, 0.9 and 0.99.

5.3. Preparation of reduced point density data

The desired point density of point clouds depends on the application on hand. On the other hand, different scanner may also provide different point density data. Therefore, testing of the algorithm with different point density dataset is important to understand the performance of the algorithm on

various point density data. This may require different point density datasets covering the same area. However, this may not always be feasible to acquire different point density datasets for the same area. Also, this is not demanded by any application as reduced point density dataset can always be prepared by removing some points from the highest point density dataset.

The most usual way to reduce the point density is to remove points from the original higher density dataset that fall within some distance from an arbitrarily chosen point. In case of airborne laser scanning dataset, the point density can be measured in planimetric where as in terrestrial laser dataset; this should be measured along the face of the plane as planimetric measure does not represent the characteristics of the terrestrial laser data. As the orientation of the plane is not always known in unstructured point clouds, removing points that fall inside a sphere of certain radius is logical option and chosen in this thesis to reduce the point density of the data. This radius can be considered as minimum point spacing among points.

Point density varies among different datasets mentioned in section 4.2; the reduced point density data is prepared accordingly. A programme is developed based on the above mentioned concept to reduce the point density. The different reduced point density dataset is presented in Table 5-1. For experimental purpose, different point spacing is chosen considering the percentage of reduction of points. In this work, the original datasets represent the highest point density datasets available for evaluation purpose.

Table 5-1: Reduced point density data

Dataset	Vlaardingen	
Minimum Point Spacing (m)	**Number of Points**	**% of Original Points**
Original	371910	100.00
0.01	332125	89.30
0.04	104779	28.17
0.08	37447	10.07

Dataset	German Building	
Minimum Point Spacing (m)	**Number of Points**	**% of Original Points**
Original	68189	100
0.04	67921	99.60
0.06	36584	53.65
0.08	21364	31.33

Dataset	ITC Building	
Minimum Point Spacing (m)	**Number of Points**	**% of Original Points**
Original	81212	100.00
0.4	41661	51.29
0.6	22950	28.26
1.0	10273	12.65

5.4. Reference data preparation

To test the performance of the developed algorithm, reference dataset containing the desired segments are required. This reference dataset is prepared by visually examining points on Point Cloud Mapper (PCM) software. The points falling in one planar surface and having similar colour is given a unique segment number. Out of all the possible planar surfaces present in the data, the representative reference planar surface are created considering various objects present in the data such as walls, roofs, dormer, doors, windows and parts of them considering colour similarity. This reference dataset is prepared from the highest point density available in each dataset. In preparing reference samples, especially for TLS data, some planes adjacent to the ground surface are ignored as this is subjected to noise created by the presence of undesired objects like vehicles.

To prepare reference data for reduced density point clouds, points are matched between highest density reference dataset and reduced density point clouds. Only those points from reference data, which also belongs to reduced point density data, are considered. A tool is developed to perform this task. The process is illustrated in Figure 5-1.

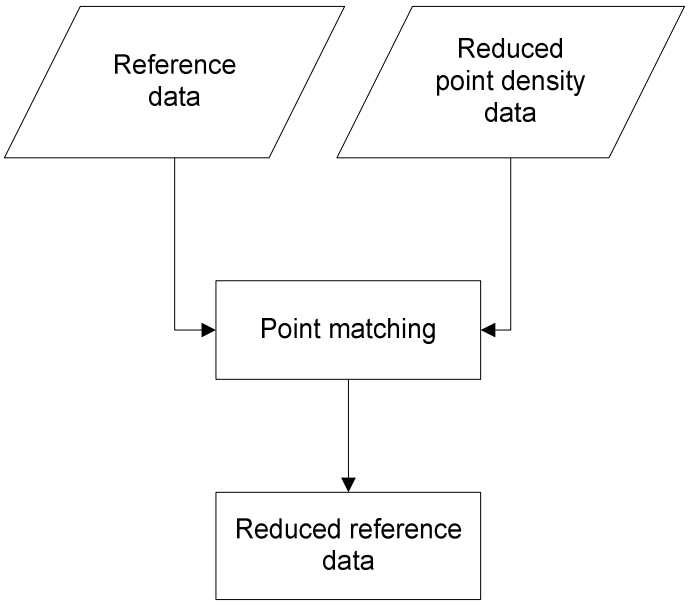
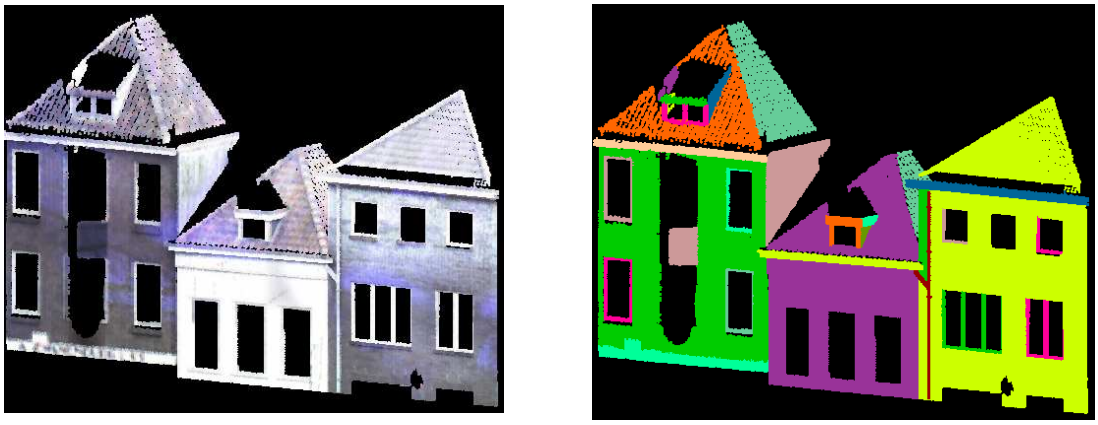


Figure 5-1: Reduced reference data preparation

Figure 5-2 to Figure 5-3 show some reference segments prepared interactively and used for evaluating performance of the developed algorithm. Table 5-2 shows the summary of the reference samples prepared.

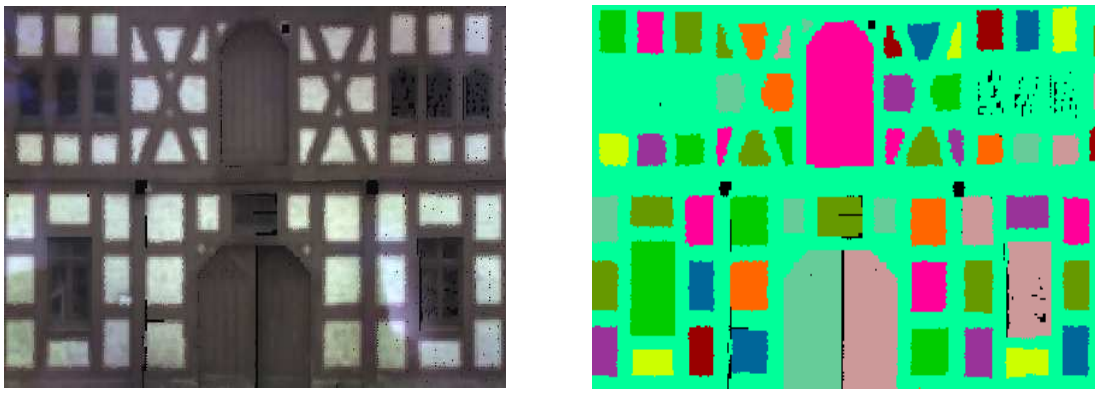
Table 5-2: Summary of reference samples

Dataset	Number of reference planes	Description
Vlaardingen data	32	The reference plane contains walls, roofs, doors, window openings and dormers.
German building data	107	It has different planar regions in a wall.
ITC building data	53	It constitutes roof planes having different orientation.



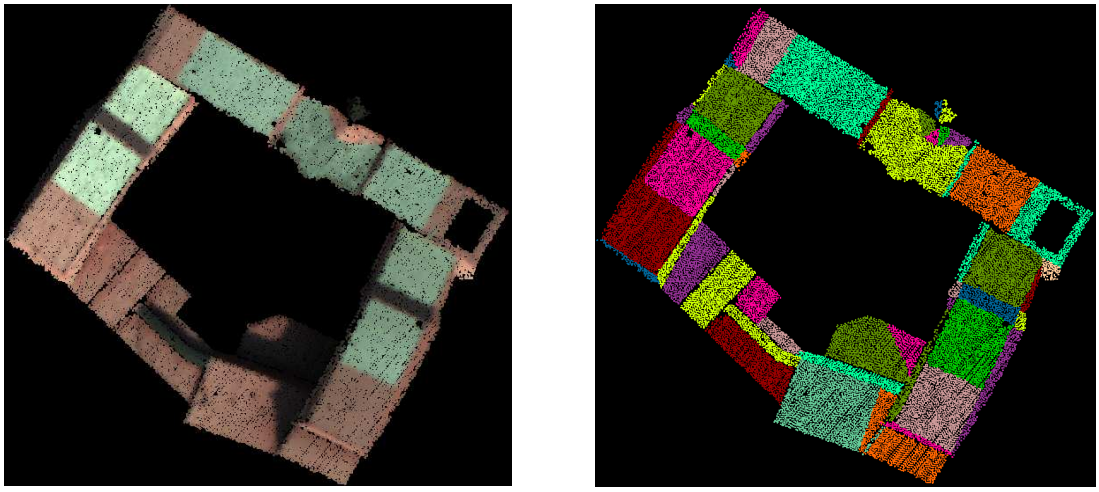
(a) (b)

Figure 5-2: Reference segments of Vlaardingen data (a) RGB colour (b) Coloured segments



(a) (b)

Figure 5-3: Reference segments of German building (a) RGB colour (b) Coloured segments



(a) (b)

Figure 5-4: Reference segments of ITC building (a) RGB colour (b) Coloured segments

5.5. Result analysis

This section presents the results of the data processing according to the framework outlined above. The segmentation parameters applied to process different point density datasets are similar to that presented in section 4.4.1. Radii are changed accordingly to accommodate the changing point spacing. The number of segments that are recorded in each instances of correct segmentation, over, under segmentation, missed segment and noisy segments are shown in Table 5-3 to Table 5-7 for different tolerances. The geometrical accuracy is presented in Table 5-8. The corresponding charts show the same results. However, to avoid the confusion from cluttered lines, only the results from original dataset are shown.

Table 5-3: Correct segmentation at different minimum point spacing

Tolerance	Number of instances of correct segmentation											
	Vlaardingen data				German building				ITC building			
	Minimum point spacing (m)				Minimum point spacing (m)				Minimum point spacing (m)			
	Original	0.01	0.04	0.08	Original	0.04	0.06	0.08	Original	0.40	0.60	1.00
0.51	15	15	15	13	96	96	94	75	38	41	43	27
0.6	14	15	15	13	95	95	94	74	38	40	43	27
0.7	14	15	14	13	94	94	93	73	39	41	40	27
0.8	12	13	14	14	92	93	91	71	35	38	35	27
0.9	11	10	10	11	79	78	75	61	25	26	29	17
0.99	3	3	2	1	32	32	25	26	5	3	3	4

Correct segmentation

The result reveals that the numbers of correctly detected segments decreases as the tolerance increases. It is obvious that at lower tolerance, fewer numbers of matching points between reference sample and its corresponding plane in the segmentation result is enough to return the instances of correct detection. Table 5-3 shows the performance of the algorithm for different tolerances. The same result is presented for original point density data in Figure 5-5 too. In Vlaardingen data, the numbers of correctly detected planes are 15 out of 32 reference samples at tolerance of 0.51. The lower instances of correctly detected segments are basically because the colour information available in the data which is not good enough. The correctly detected planar segments of German building is higher than other two test datasets i.e. 96 segments out of 107 are correctly detected at tolerance of 0.51. In case of ITC building, there are 38 out of 53 segments correctly detected at the same tolerance. The roof segments are not perfectly planar and this algorithm is designed to detect planar segments. To reduce the effect of non conformance to planar surface, the threshold of the distance to the plane was set relatively higher (0.25m during plane growing). Still, few instances of over-segmentation can be observed in the result.

The numbers of correctly detected segments till tolerance 0.8 are closer to that at the tolerance of 0.51 for all datasets. The algorithm is able to detect significant numbers of correct segments even at the highest tolerance of 0.99 in German building, where segments are in regular pattern.

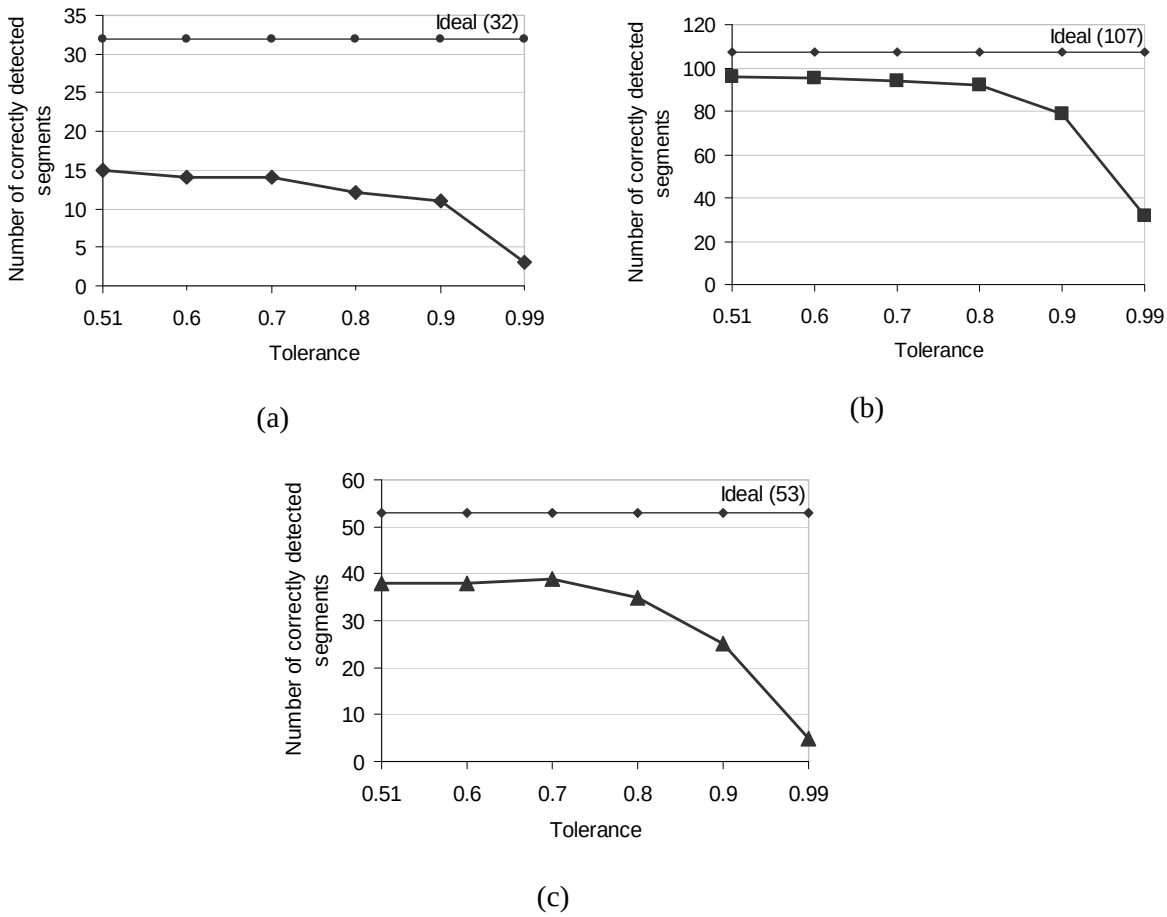


Figure 5-5: Correct segmentation (a) Vlaardingen data (b) German building (c) ITC building

Table 5-4: Over segmentation at different minimum point spacing

Tolerance	Number of instances of over segmentation											
	Vlaardingen data				German building				ITC building			
	Minimum point spacing (m)				Minimum point spacing (m)				Minimum point spacing (m)			
	Original	0.01	0.04	0.08	Original	0.04	0.06	0.08	Original	0.40	0.60	1.00
0.51	16	16	11	5	2	2	2	0	10	7	3	4
0.6	16	15	11	3	2	2	2	0	10	6	3	4
0.7	16	15	11	3	3	2	1	0	7	6	3	4
0.8	14	14	8	2	3	3	1	0	6	4	3	3
0.9	12	11	7	2	2	2	1	0	4	2	1	2
0.99	3	2	0	0	0	0	0	0	0	0	0	1

Over-segmentation

The results of over segmentation are presented in Table 5-4. Same result for original point density data is in Figure 5-6. The Vlaardingen and ITC building data show higher instances of over segmentation than in German building. In Vlaardingen data, colour varies on the same surface. For example, colour on the same wall surface varies significantly. This has caused the over-segmentation. The algorithm is designed to reduce the influence of such variation considering the colour homogeneity in local region. Still, the result shows that the number of instances of over-segmentation

(i.e. 16 at tolerance of 0.51) is even higher than the number of instances of correct segmentation (i.e. 15 at tolerance of 0.51). One of the main reasons behind it is that the reference samples are optimistically prepared. For example, some colour variation in walls or window frames are ignored as it is quite complex to visually demark the segments created by colour variations.

In case of ITC building, some instances of over segmentation are created by non-conformance of roof segments to planar surface. Another important observation here is that some roofs are segmented into more than one segment because of the shadow. This is illustrated in Figure 5-7 marked by a circle.

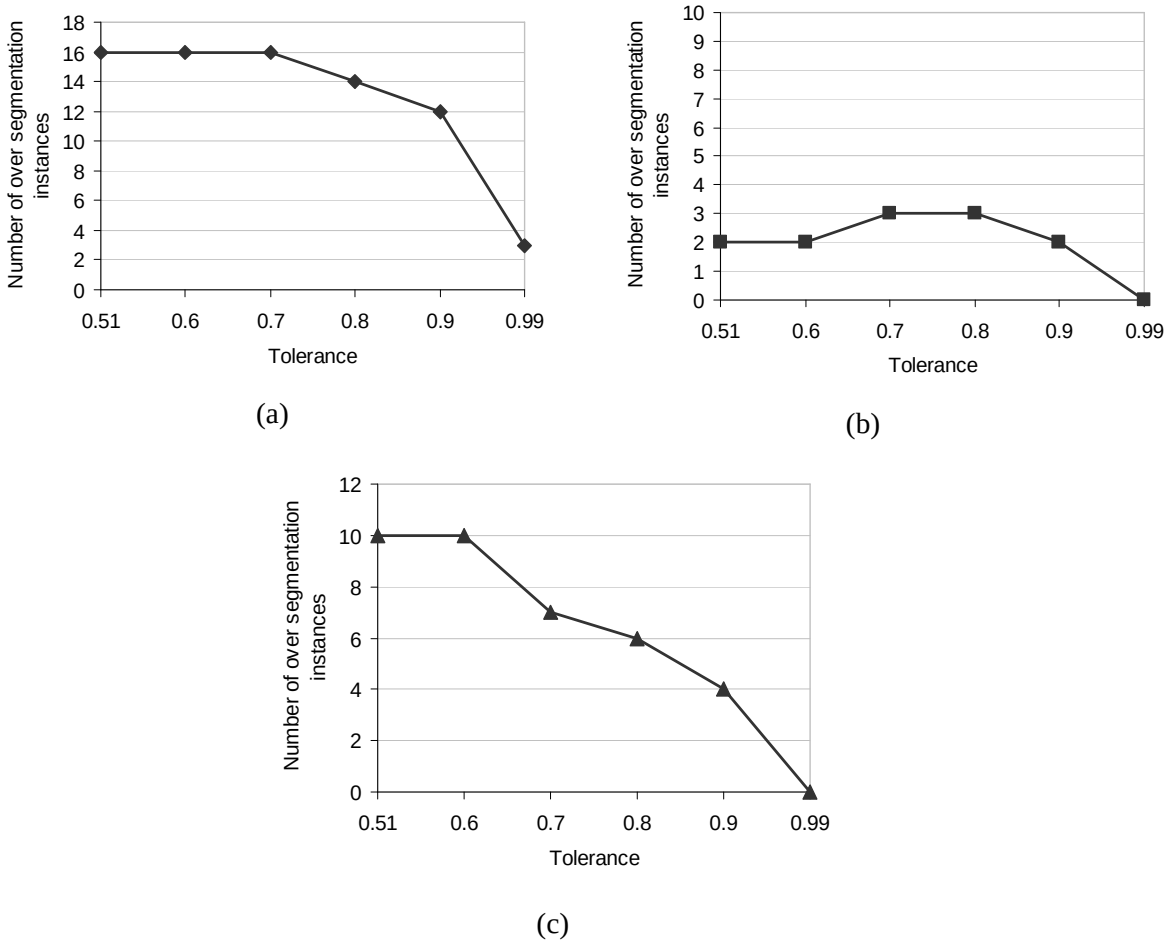
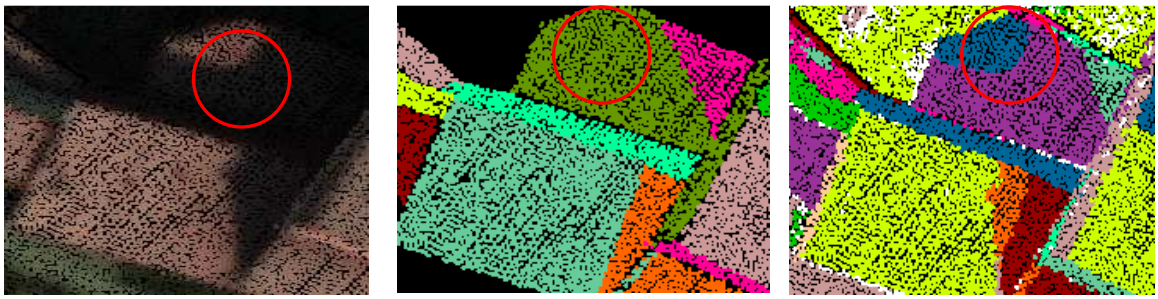


Figure 5-6: Over segmentation (a) Vlaardingen data (b) German building (c) ITC building



(a) (b) (c)

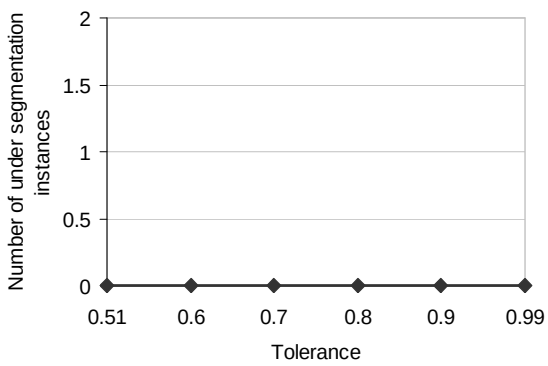
Figure 5-7: Over segmentation by shadow (a) Coloured point clouds (b) Reference segments (c) Resulted segments

Under-segmentation

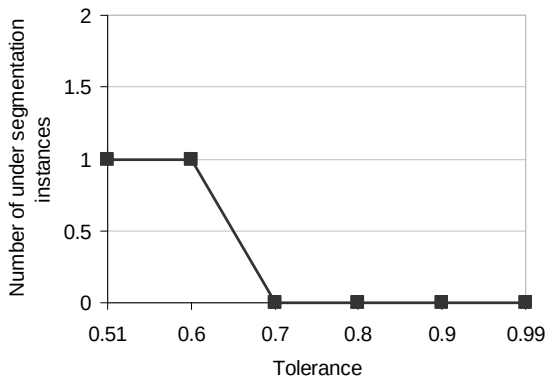
There are only few or no instances of under-segmentation in all datasets. The result is presented on Table 5-5. Figure 5-8 shows the same result for original point density data. This means that the algorithm is performing well in avoiding under-segmentation.

Table 5-5: Under segmentation at different minimum point spacing

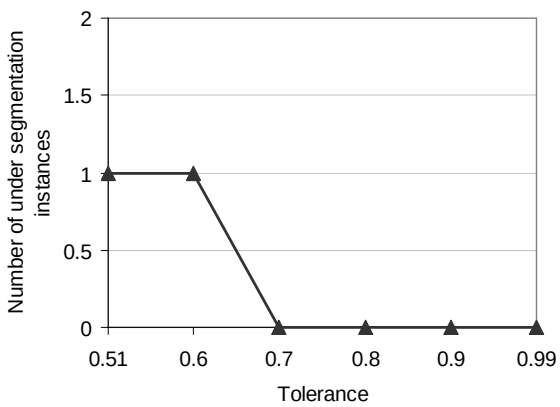
Tolerance	Number of instances of under segmentation											
	Vlaardingen data				German building				ITC building			
	Minimum point spacing (m)				Minimum point spacing (m)				Minimum point spacing (m)			
	Original	0.01	0.04	0.08	Original	0.04	0.06	0.08	Original	0.40	0.60	1.00
0.51	0	0	0	2	1	1	1	2	1	1	1	2
0.6	0	0	0	2	1	1	1	2	1	1	1	2
0.7	0	0	0	2	0	1	1	2	0	0	1	0
0.8	0	0	0	1	0	0	1	2	0	0	0	0
0.9	0	0	0	1	0	0	0	2	0	0	0	0
0.99	0	0	0	0	0	0	0	0	0	0	0	0



(a)



(b)



(c)

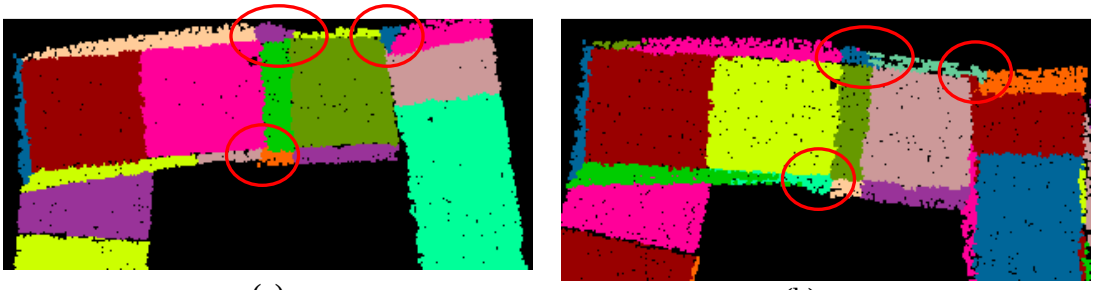
Figure 5-8: Under segmentation (a) Vlaardingen data (b) German building (c) ITC building

Missed segments

In lower tolerance value, there are fewer instances of missed segments in all test datasets. For strict tolerances of 0.9 and higher, missed planes increases rapidly. This is because of the fact that at higher tolerances, there should be strict matching of points between reference and the corresponding result. The missed segments at lower tolerances are of smaller size. Small segments, for example windows in Vlaardingen data are segmented into more than one small segment causing the instances of missed segments. The results of missed segments are presented in Table 5-6. The same results for original point density dataset are shown in Figure 5-10. Some of the small roof parts missed at tolerance of 0.8 for ITC building is marked by circle in Figure 5-9.

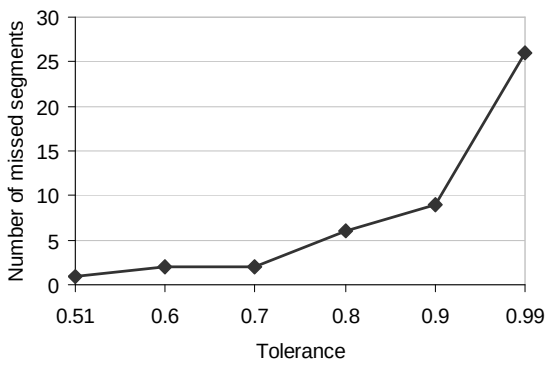
Table 5-6: Missed segments at different minimum point spacing

Tolerance	Number of instances of missed segments											
	Vlaardingen data				German building				ITC building			
	Minimum point spacing (m)				Minimum point spacing (m)				Minimum point spacing (m)			
	Original	0.01	0.04	0.08	Original	0.04	0.06	0.08	Original	0.40	0.60	1.00
0.51	1	1	6	9	2	2	2	14	3	3	4	18
0.6	2	2	6	11	5	5	4	16	3	5	5	18
0.7	2	2	7	11	10	7	8	19	7	6	8	22
0.8	6	5	10	13	12	11	11	25	12	11	15	23
0.9	9	11	15	16	26	27	31	37	24	25	23	34
0.99	26	27	30	31	75	75	82	81	48	50	50	48

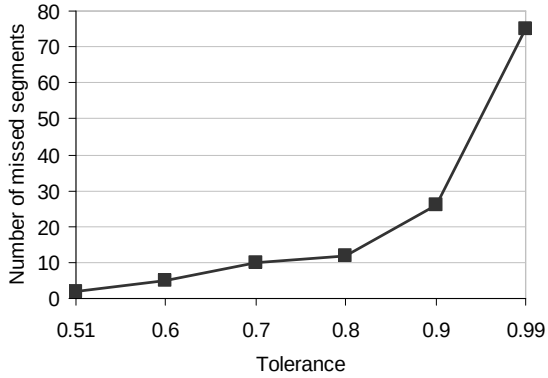


(a) (b)

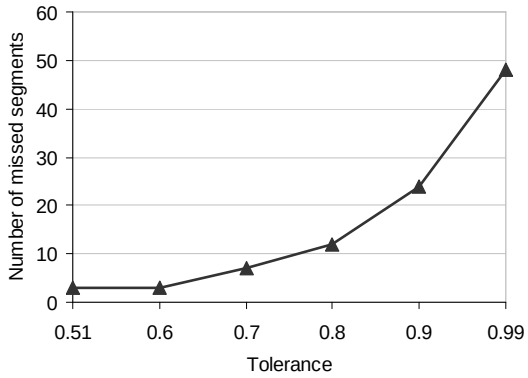
Figure 5-9: Missed segments at tolerance of 0.8 for ITC building (a) Reference segments (b) Result segments



(a)



(b)



(c)

Figure 5-10: Missed segments (a) Vlaardingen data (b) German building (c) ITC building

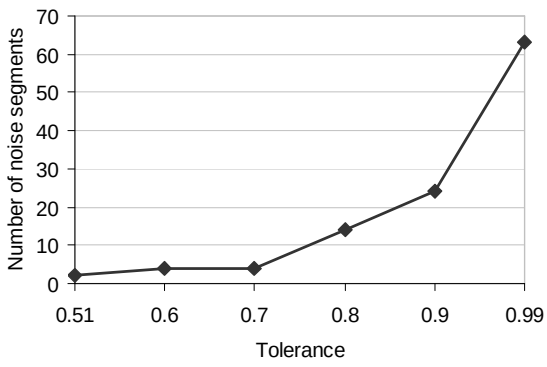
Table 5-7: Noisy segments at different minimum point spacing

Tolerance	Number of instances of noisy segments											
	Vlaardingen data				German building				ITC building			
	Minimum point spacing (m)				Minimum point spacing (m)				Minimum point spacing (m)			
	Original	0.01	0.04	0.08	Original	0.04	0.06	0.08	Original	0.40	0.60	1.00
0.51	2	2	7	4	7	6	4	4	4	3	0	0
0.6	4	4	9	9	8	7	4	5	4	6	0	0
0.7	4	5	10	9	10	9	7	11	10	6	3	2
0.8	14	13	16	11	13	11	9	13	16	14	9	4
0.9	24	29	30	14	29	29	31	23	30	30	19	16
0.99	63	85	65	35	92	88	89	60	60	57	47	31

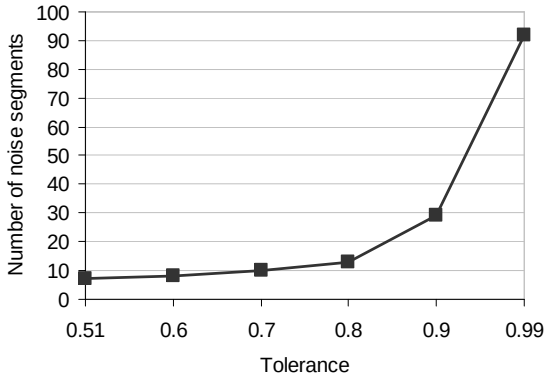
Noisy segments

For smaller tolerance value, for example, less than 0.8, the noisy segments are relatively fewer for all datasets. As the tolerances increase, the noisy instances are increasing rapidly. The results are presented in Table 5-7. Figure 5-11 is the plot of same result for the original point density data. There are some noise segments towards the edges and even on the interiors of larger regions. Generally,

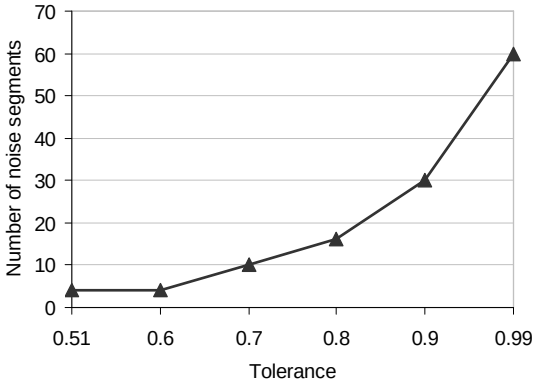
these segments are resulted because of the colour variations. Some instances are shown in Figure 5-12 where we can see linear edge segment in (a) and small segments inside large wall segment in (b).



(a)

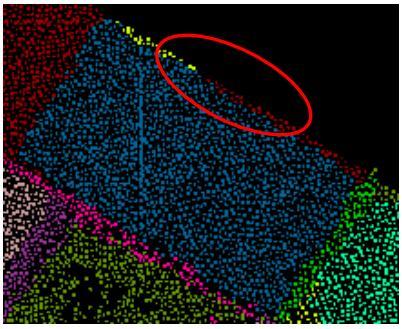


(b)

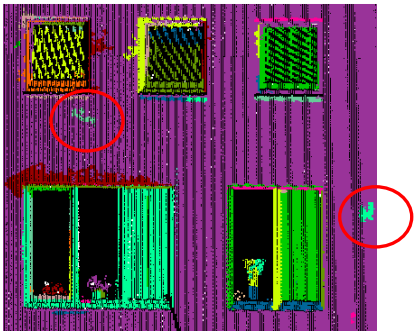


(c)

Figure 5-11: Noisy segments (a) Vlaardingen data (b) German building (c) ITC building



(a)



(b)

Figure 5-12: Noisy segments (a) towards edge (b) interior of region

Geometrical accuracy

The geometrical accuracy of angle is presented in Table 5-8 and Figure 5-13 for original point density data. In case of Vlaardingen and ITC building, the errors are higher than one degree for lower tolerances. But for German building, these values are lower for all tolerances. The decreasing trend of angles as tolerance increases shows that the planes detected at higher tolerances are more accurate. In case of Vlaardingen data, the sudden reduction of angle error at tolerance 0.8 does not reveal any conclusive information here as the angle error is calculated from few instances of correct segments. Another observation for the same data is that the angle error is high (6.69^0) at minimum point spacing of 0.08m. By scrutinizing the result, it is found that two dormer segments are created erroneously. While not counting those two segments, the angle error remains similar as in other minimum spacing values.

Table 5-8: Geometrical accuracy of segments at different minimum point spacing

Tolerance	Root Mean Square Error of Angle (degree)											
	Vlaardingen data				German building				ITC building			
	Minimum point spacing (m)				Minimum point spacing (m)				Minimum point spacing (m)			
	Original	0.01	0.04	0.08	Original	0.04	0.06	0.08	Original	0.40	0.60	1.00
0.51	2.23	2.29	1.33	6.69	0.24	0.24	0.35	0.78	1.25	1.23	1.01	0.7
0.6	2.17	2.32	1.33	6.69	0.23	0.23	0.35	0.62	1.25	1.14	1.01	0.7
0.7	2.17	2.32	1.05	6.69	0.23	0.22	0.47	0.60	1.23	1.13	0.73	0.6
0.8	0.45	1.07	2.39	6.40	0.22	0.22	0.30	0.34	0.96	1.15	0.63	0.5
0.9	0.19	0.20	1.09	6.79	0.19	0.19	0.16	0.18	0.64	0.44	0.47	0.1
0.99	0.01	0.01	0.03	0.02	0.02	0.01	0.01	0.00	0.01	0.02	0.00	0

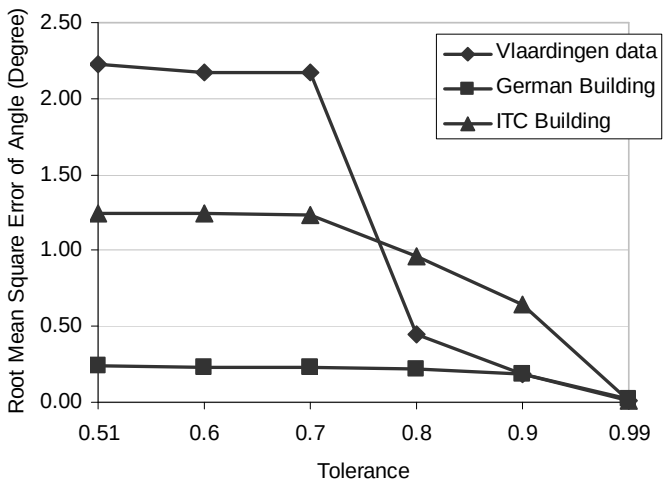


Figure 5-13: Geometrical accuracy of segments of original point density data

Performance at different radius

Different parameters need to be adjusted to produce the optimal result. Basically, k-neighbours are used as neighbouring points instead of considering all the points that falls inside the radius of input threshold to speed up the process. By keeping k-neighbours constant, seed selection and growing radii are changed gradually to evaluate the impact of changing neighbourhood size. The ranges of radius values are decided by examining the result from the experiments. The seed selection and growing radii are changed equally. Other parameters have been kept constant during the process. The numbers of correctly detected segments from original point density datasets with different seed selection radius are presented in Table 5-9. By observing the results, 0.15m for Vlaardingen data, 0.25m for German building and 1.5m for ITC building are considered as optimal radius.

Table 5-9: Correctly detected segments of original point density data at different seed radius

Tolerance	Number of instances of correct segmentation											
	Vlaardingen data				German building				ITC building			
	Radius in meter				Radius in meter				Radius in meter			
	0.10	0.15	0.20	0.25	0.20	0.25	0.30	0.40	1.00	1.25	1.50	2.00
0.51	12	15	13	12	95	96	96	96	35	37	38	37
0.6	12	14	12	12	94	95	95	95	35	37	38	37
0.7	13	14	12	12	91	94	94	94	35	38	39	37
0.8	13	12	11	11	90	92	93	93	33	35	35	34
0.9	10	11	9	8	73	79	79	78	22	26	25	24
0.99	3	3	3	2	30	32	35	35	6	6	5	5

Performance at different point spacing

Performances at different minimum point spacing were evaluated for all datasets which are presented in Table 5-3 to Table 5-8. Figure 5-14 shows the correctly detected segments at different minimum point spacing for German building data. At larger spacing, there is decreasing trend of correctly detected segments. In general, points in small segments are left un-segmented in larger spacing. The reason behind this is that for small segments, the number of points will be fewer in larger point spacing, which is not sufficient to detect as a segment. This situation is illustrated in Figure 5-15 where points on small segments are left un-segmented but there are sufficient numbers of points in reference sample. General trend of increasing number of missed segments with increased point spacing also justifies above assertion.

In case of ITC building data (Figure 5-16) there are slight increases in number of correctly detected segments as minimum point spacing increases (at 0.4m and 0.6m spacing). At larger spacing, small details caused by colour variation were removed while in original density point clouds those were detected as small segments producing over-segmentation or noisy-segmentation. At 1.0m spacing, the correctly detected segments decreased.

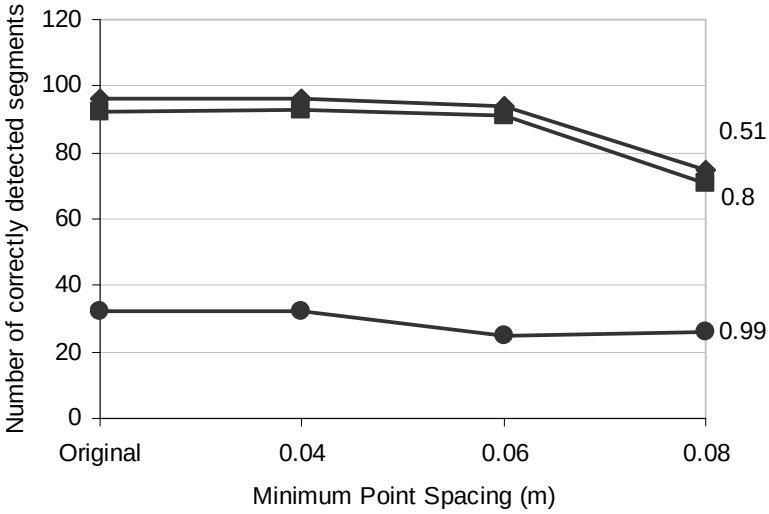
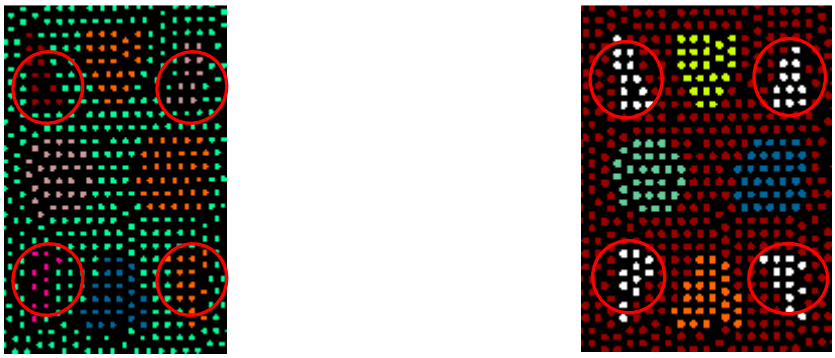


Figure 5-14: Correctly detected segments at different point spacing of German building



(a) (b)

Figure 5-15: Un-segmented points at spacing of 0.08m for German building (a) reference segments (b) result segments

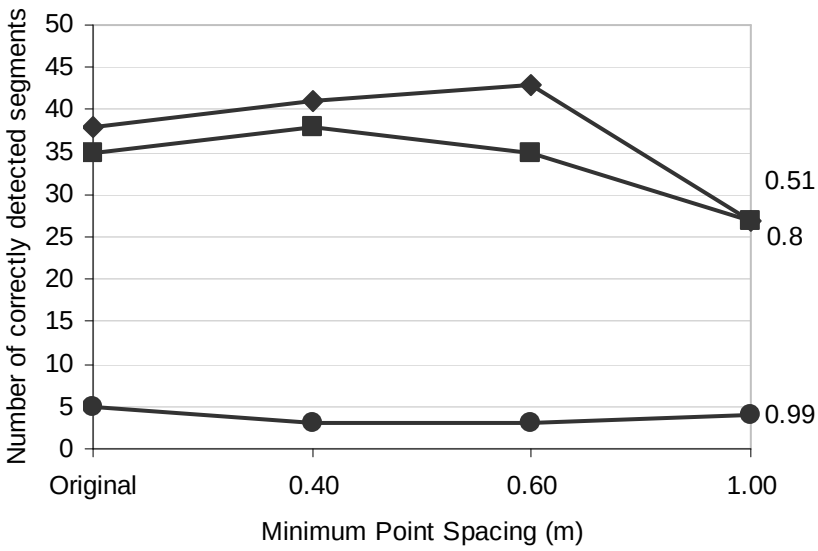


Figure 5-16: Correctly detected segments at different point spacing of ITC building

5.6. Processing speed

The processing speed of algorithm depends on the number of points as well as the number of planes present in the data. The algorithm is implemented with C++ programming language. The time taken to process different dataset is presented in Table 5-10. The processing time is based on a desktop computer with a Pentium 4 processor running at 3.20GHz and 1GB RAM.

Table 5-10: Processing time in seconds

Dataset	Number of points (planes)	Time in seconds
Vlaardingen data	371910 (592)	117
German Building data	68189(246)	23
ITC Building data	81212(369)	32

5.7. Concluding remarks

Different performance evaluation metrics are defined to evaluate the segmentation results. The algorithm is tested on different point density datasets. The results are evaluated by comparing the result segments with interactively prepared reference samples. The results show the varying number of instances of correct segmentation. This is obvious result as the geometrical and colour information varies on test datasets. The algorithm is able to minimize the effect of some colour variation. Still, the adverse effects of colour variation are observed. Larger number of over-segmentation in Vlaardingen data is mainly due to the effect of colour variation. This result is more related to the quality of data than the algorithm itself. The algorithm is not able to manage the effect of strong shadow.

The usability of the results from segmentation process depends on the intended application. The good segmentation algorithm is one which can detect all segments correctly at the highest tolerance value. The metrics defined above to quantify the performance of the developed algorithm could have different meanings (Hoover et al., 1996). Rabbani et al. (2006) preferred under-segmentation instead of over-segmentation for the problem of segmenting point clouds from industrial installations. On the other hand, Pu and Vosselman (2006) argue that over-segmentation is preferred while segmenting point clouds for detailed building reconstruction as over-segmented parts can always be combined in later stages but under-segmented object surfaces can hardly be split. However, the investigation of actual effects of the segmentation results produced by this research in particular application such as building reconstruction is out of the scope this work.

6. Conclusions and Recommendations

6.1. Conclusions

The main objective of this research is to develop segmentation algorithm for coloured point cloud data. The first research question is related to the literature review of the existing segmentation methods. The state-of-the-art of the segmentation methods proposed for the segmentation of point clouds has been reviewed and the methods are categorized based on their general characteristics. By this, the first research question has been answered. To deal with the second research question, the review of colorimetric information has been presented. This includes the review of colour spaces and the colour similarity measurement criteria. The third research question is about the development of a segmentation algorithm. A new segmentation strategy is developed by integrating geometrical and colour information in a single step process. A surface growing based algorithm has been proposed to segment coloured point clouds. The last research question is about the performance evaluation of the algorithm. The algorithm is tested on the datasets acquired from terrestrial as well as airborne laser scanning systems. First, the results have been discussed based on the visual examination. Finally, the performance of the algorithm over various point density datasets was assessed by defining performance evaluation metrics. The following conclusions are drawn:

- Geometrical and colour information can be combined in segmentation process while treating both spaces separately. The combination of geometrical and colour information lead to more meaningful segmentation results. Hence, the use of colour information is advantageous in segmentation of point clouds data.

- The use of colour information imposes some limitations. This limitation is more related to the quality of the colour information in the data. The variation of colour on object surface, effect of shadow and the presence of additional objects (such as cars in TLS data) create irrelevant segments. The algorithm is able to minimize the effect of some colour variation. The adverse effects of strong shadow are not managed fully. For example, shadow tends to produce more segments. The use of colour has also produced some small segments towards the edges.

- The performance of the algorithm is dependent to the geometrical as well as colour information. The algorithm requires optimisation of parameters for each dataset. Particularly, for tolerances of 0.51 to 0.8, the results are comparable. For the highest tolerance of 0.99, there are no or low instances of correct or over-segmentation whereas higher numbers of missed or noisy segments are produced for all the datasets.

- The performance of the algorithm varies with point density of the dataset. In general, lower the point density; lower the number of correct segments algorithm produces. In larger spacing, there are higher numbers of missed segments where points in small segments are generally left un-segmented.

- During parameter selection of the algorithm, all possible combinations of parameters that produce the best result are not investigated. The parameters of the algorithm are optimized empirically. It is needed further investigation to know the actual relationship between the parameters and their actual influence on the segmentation results.

6.2. Recommendations

This research showed that there are distinct benefits of using colour information in segmentation. However, accuracy of this algorithm is governed not only by the geometrical information but also by the quality of colour information available in point clouds. Some recommendations for further research are as follows:

- As the effect of shadow is undesirable in segmentation, the colour similarity measurement that minimizes the effect of shadow should further be investigated.

- Further investigation can be carried out for automatic determination of different parameters used in segmentation. Additional research can be directed towards the adaptation of different parameters according to the local situations. The investigation of relationship between parameters can be subject of further research.

- Hough transform is used in this work to detect seed plane, it is recommended to investigate RANSAC technique for the same process. The use of RANSAC for seed plane selection may be computationally faster than Hough transform.

- Though the issue of colour quality was not dealt directly in this research but the quality of colour itself affects the result of the proposed segmentation method. Higher resolution camera would improve the quality of colour information. In case of simultaneous capturing of coloured point clouds, the weather condition that produce best colour should be chosen. Specially, in case of terrestrial laser scanning, if laser points taken from different stations are to be merged together, special care should be given to the points in overlapping area to avoid the colour variation of points taken from different stations and to maintain the uniform natural colour.

References

Abdelhafiz, A., Riedel, B. and Niemeier, W., 2005. Towards a 3D True Colored Space by the Fusion of Laser Scanner Point Cloud and Digital Photos. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 5/W17, Venice, Italy.

Abmayr, T. et al., 2004. Realistic 3D Reconstruction – Combining Laserscan Data with RGB Color Information. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXV, part B, Istanbul, Turkey, pp. 549.

Belton, D. and Lichti, D.D., 2006. Classification and segmentation of terrestrial laser scanner point clouds using local variance information. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 5, Dresden, Germany, pp. 44-49.

Böhm, J. and Becker, S., 2007. Automatic Marker-Free Registration of Terrestrial Laser Scans using Reflectance Features, Proceedings of 8th Conference on Optical 3D Measurment Techniques, Zurich, Switzerland, pp. 338-344.

Bretar, F. and Roux, M., 2005. Hybrid image segmentation using LiDAR 3D planar primitives. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 3/W19, Enschede, the Netherlands, pp. 232.

Chau, C.-P. and Siu, W.-C., 2004. Generalized Hough Transform Using Regions with Homogeneous Color. International Journal of Computer Vision, 59(2): 183-199.

Cheng, H.D., Jiang, X.H., Sun, Y. and Wang, J., 2001. Color image segmentation: advances and prospects. Pattern Recognition, 34(12): 2259-2281.

Cree, M.J., 2004. Observations on Adaptive Vector Filters for Noise Reduction in Color Images. IEEE Signal Processing Letters, 11(2): 140-143.

Dold, C. and Brenner, C., 2004. Automatic Matching of Terrestrial Scan Data as a Basis for the Generation of Detailed 3D City Models. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXV, part B3, Istanbul, Turkey, pp. 1091-1096.

Filin, S., 2002. Surface clustering from airborne laser scanning data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXIV, part 3A/B, Graz, Austria, pp. 119-124.

Filin, S. and Pfeifer, N., 2006. Segmentation of airborne laser scanning data using a slope adaptive neighborhood. ISPRS Journal of Photogrammetry and Remote Sensing, 60(2): 71-80.

Geibel, R. and Stilla, U., 2000. Segmentation of laser-altimeter data for building reconstruction: Comparison of different procedures. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXIII, part B3, Amsterdam, The Netherlands, pp. 326-334.

Gorte, B.G.H., 2002. Segmentation of tin-structured surface models, Joint Conference on Geo-spatial theory, Processing and Applications, Ottawa, Canada, 8 - 12 July 2002.

Hoover, A. et al., 1996. An Experimental Comparison of Range Image Segmentation Algorithms. IEEE Transactions on Pattern Analysis and Machine Intelligence archive, 18 (7): 673 - 689.

Koschan, A. and Abidi, M., 2001. A Comparison of Median Filter Techniques for Noise Removal in Color Images. In: D. Paulus and J. Denzler (Editors), Proc. 7th German Workshop on Color Image Processing, pp. 69-79, Erlangen, Germany, October 2001.

Lerma, J.L. and Biosca, J.M., 2005. Segmentation and filtering of the laser scanner data for cultural heritage. CIPA 2005 XX International Symposium, 26 September – 01 October, 2005, Torino, Italy.

Lucchese, L. and Mitra, S.K., 2001. Color Image Segmentation: A State-of-the-Art Survey. Image Processing, Vision, and Pattern Recognition, Proc. of the Indian National Science Academy (INSA-A), 67 A(2): 207-221.

Lukac, R., 2003. Adaptive vector median filtering. Pattern Recognition Letters, 24(12): 1889-1899.

Maas, H.-G. and Vosselman, G., 1999. Two algorithms for extracting building models from raw laser altimetry data. ISPRS Journal of Photogrammetry and Remote Sensing, 54(2-3): 153-163.

Nyaruhuma, A.P., 2007. Performance analysis of algorithms for detecting roof faces in airborne laser scanner data. MSc Thesis, ITC, Enschede, 80 pp.

Oude Elberink, S.J. and Vosselman, M.G., 2006. Adding the Third Dimension to a Topographic Database Using Airborne Laser Scanner Data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 3, Bonn, Germany, pp. 92-97.

Overby, J., Bodum, L., Kjems, E. and Ilsoe, P.M., 2004. Automatic 3d Building Reconstruction from Airborne Laser Scanning and Cadastral Data Using Hough Transform. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXV, part B3, Istanbul, Turkey.

Perera, G.S.N., 2007. Segment based filtering of LASER scanner data. MSc Thesis, ITC, Enschede, 104 pp.

Przybilla, H.-J., 2006. Fusion of terrestrial laserscanning and digital photogrammetry. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 5, Dresden, Germany.

Pu, S. and Vosselman, M.G., 2006. Automatic extraction of building features from terrestrial laser scanning. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 5, Dresden, Germany.

Rabbani, T., van den Heuvel, F.A. and Vosselman, M.G., 2006. Segmentation of point clouds using smoothness constraints. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 5, Dresden, Germany, pp. 248-253.

Roggero, M., 2002. Object Segmentation with Region Growing and Principal Component Analysis. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXIV, part 3A, Graz, Austria, pp. 289-294.

Schnabel, R., Wahl, R. and Klein, R., 2007a. Efficient RANSAC for Point-Cloud Shape Detection. Computer Graphics Forum, 26(2): 214-226.

Schnabel, R., Wahl, R. and Klein, R., 2007b. Shape Detection in Point Clouds. Computer Graphics Technical report, No. CG-2006-2, University of Bonn, Bonn, Germany, http://cg.informatik.uni-bonn.de/docs/publications/2006/cg-2006-2.pdf (Accessed September 21, 2007).

Schnabel, R., Wahl, R., Wessel, R. and Klein, R., 2007c. Shape Recognition in 3D Point Clouds. Computer Graphics Technical report, No. CG-2007-1, University of Bonn, Bonn, Germany,http://cg.informatik.uni-bonn.de/docs/publications/2006/cg-2006-2.pdf (Accessed September 21, 2007).

Sithole, G., 2005. Segmentation and classification of airborne laser scanning data. PhD Thesis, Technical University of Delft, Delft, 327 pp.

Skarbek, W. and Koschan, A., 1994. Colour Image Segmentation - A Survey, Technical Report 94-32. Institute for Technical Informatics, Technical University of Berlin, Germany.

Slob, S. and Hack, H.R.G.K., 2004. 3D terrestrial laser scanning as a new field measurement and monitoring technique, In: Engineering geology for infrastructure planning in Europe : a European perspective / editor H.R.G.K. Hack, R. Azzam, R. Charlier. - Berlin etc. : Springer, 2004. (Lecture Notes in Earth Sciences ; 104) pp. 179-190.

Tarsha-Kurdi, F., Landes, T. and Grussenmeyer, P., 2007. Hough-Transform and Extended RANSAC Algorithms for Automatic Detection of 3D Building Roof Planes from Lidar Data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 3/W52, Espo, Finland, pp. 407-412.

Tóvári, D., 2006. Segmentation Based Classification of Airborne Laser Scanner Data. PhD Thesis, Universität Karlsruhe, Karlsruhe, Germany.

Tóvári, D. and Pfeifer, N., 2005. Segmentation based robust interpolation - a new approach to laser data filtering. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 3/W19, Enschede, the Netherlands, pp. 79-84.

Tremeau, A. and Borel, N., 1997. A region growing and merging algorithm to color segmentation. Pattern Recognition, 30(7): 1191-1203.

Vardavoulia, M.I., Andreadis, I. and Tsalides, P., 2001. A new vector median filter for colour image processing. Pattern Recognition Letters, 22(6-7): 675-689.

Verbree, E., Zlatanova, S. and Dijkman, S., 2005. Distance-Value-Added Panoramic Images as the Base Data Model For 3D-GIS. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 5/W8, Berlin, Germany.

Vosselman, G. and Dijkman, S., 2001. 3D Building Model Reconstruction from Point Clouds and Ground Plans, International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXIV, part 3/W4, Annapolis, pp. 37-43.

Vosselman, M.G., Gorte, B.G.H., Sithole, G. and Rabbani, T., 2004. Recognising structure in laser scanning point clouds, International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI, part 8/W2, Freiburg, Germany, pp. 33-38.

Wesolkowski, S.B., 1999. Color Image Edge Detection and Segmentation: A Comparison of the Vector Angle and the Euclidean Distance Color Similarity Measures. MSc Thesis, University of Waterloo, Ontario, Canada.