A segment-based approach for digital terrain model derivation in airborne laser scanning data

Yuxiang He March, 2010

A segment-based approach for digital terrain model derivation in airborne laser scanning data

by

Yuxiang He

Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfillment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation, Specialisation: (Geoinformatics)

Thesis Assessment Board

Chairman:Prof. Dr. A. SteinExternal examiner:Dr. B. HöfleSupervisor:Prof. Dr. M.G. VosselmanSecond supervisor:Dr. M. Rutzinger



INTERNATIONAL INSTITUTE FOR GEO-INFORMATION SCIENCE AND EARTH OBSERVATION ENSCHEDE, THE NETHERLANDS

Disclaimer

This document describes work undertaken as part of a programme of study at the International Institute for Geo-information Science and Earth Observation. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the institute.

Dedicated to My Dearest family

Abstract

A method for automatic extraction of Digital Terrain Model (DTM) from huge laser scanning data is presented.

With the characteristics of LiDAR system, raw point clouds represent both terrain and non-terrain surface. In order to generate DTM, several methods were developed to remove non-terrain points. Algorithms for removing non-terrain points are named as filtering. The filtering method can be categorized as point-based and segment-based algorithms. Point-based filtering can not deal with landscape with discontinuities. Segment-based filtering, on the other hand, generates segments by clustering points based on surface fitting and uses topological and geometric properties for classification. Segment-based algorithms, by global looking of surroundings, can give more reliable results.

Traditionally, filtering algorithms are performed and tested in small site. For the huge amount of point clouds, applying segmentation or segment-based filtering can not accomplish in one go in physical computer memory.

To extract DTM from huge amount of LiDAR data, three major steps are involved. First, the whole datasets is split into several small overlapping tiles. For each tile, by removing wall and vegetation points, accurate segments are found. The segments from all tiles are assigned unique segment number.

In the following step, topological descriptions for the segment distribution pattern and height jump between adjacent segments are identified in each tile. Based on the topology and geometry, segment-based filtering algorithm is performed for classification in each tile. Then, based on the spatial location of the segment in one tile, two confidence levels are assigned to the classified segments.

The segments with low confidence level are because of losing geometric or topological information in one tile. Thus, a combination algorithm is generated to detect corresponding parts of incomplete segment from multiple tiles. Then another classification algorithm is performed for these segments. The result of these segments will have high confidence level. After that, all the segments in one tile have high confidence level of classification result. The final DTM will add all the terrain segments and avoid duplicate points.

Keywords:

Huge ALS datasets, Splitting, Overlap, Segmentation, combination algorithm, Classification

Acknowledgements

I would like to take this opportunity to appreciate the people who help me during this thesis research.

First, I would like to express my sincere gratitude to my first supervisor Prof. Dr. Ir. M.G. Vosselman for the valuable advice, guidance and encouragement.

And also, my sincere appreciations are due to my second supervisor Dr. Martin Rutzinger. He devotes lots of time on my thesis and gives expert suggestions.

It is the time to express my deeply thanks to my parents. You always remind me of the health and diet. Thanks for give me the opportunity to come here. Your encouragements are always in my heart. You give me more than a life.

I am thankful to Ms. Tian Yixiang, Mr. Pu Shi, Ms. Li Xia, Mr. Zhong Lei, Ms. Xiao Jing, Mr. Ir. Sander Oude Elberink, Mr. Phem and Ms. Tian Tina for their kind help. I am specially thankful to Mr. Zhou Liang for your patience. You are the encyclopedia for me.

Thanks my TOPMAP colleagues. They are Janak Raj Joshi, Malakai, Arun and Abdulmain. We were fighting together.

I would like to thank all Chinese in ITC. I am feeling at home with you. Especially, Prof. Dang Xinghai, Dr. Wu Huanping, Yin Lei, Wei Xuebin, Li You, Wu jiexia, Wang Xi, Yang Zhenshan, Yang Fengfan, Liu Zhuoran, Ding Siqi, Cao Zhouming, Dai Li, Zhang Qiuju, Cheng Fangfang and Hao Pu.

Last but not least, my heartfelt thanks go to my dear girl friend Zixue for always understanding and encouragement. I dedicate this thesis to you.

Yuxiang He Enschede, February 2010

Table of contents

1. Intro	duction	1
1.1.	Digital Terrain Model	1
1.2.	Motivation and problem statement	1
1.3.	Research identification	2
1.3.1	. Research objectives	2
1.3.2	Research questions	3
1.4.	Innovation aimed at	3
1.5.	Structure of thesis	3
2. Revie	ew of literature	5
2.1.	Introduction	5
2.2.	Terrain points extraction	5
2.2.1	. Morphological filter	5
2.2.2	Surface-based filter	6
2.2.3	S. Segment-based filter	8
2.2.4	Full-waveform exploitation	10
2.2.5	Comparison current filtering algorithms	11
2.3.	Technique of combination images	12
2.4.	Summary	14
3. Prop	osed method	15
3.1.	Introduction	15
3.2.	Preprocessing	16
3.2.1	Dividing datasets	16
3.2.2	Removing wall and vegetation points	17
3.2.3	Smooth segmentation	18
3.2.4	. Unique segment number	19
3.3.	Classification in one tile	19
3.3.1	. Designing filter framework	20
3.3.2	. Topological description	21
3.3.3	. Filtering	23
3.4.	Using information from multiple tiles	31
3.4.1	Classification confidence	31
3.4.2	. Finding corresponding segments	33
3.4.3	Classifying incomplete segment	35
3.5.	Merging all tiles	35
3.6.	Summary of the algorithm	36
4. Imple	ementation and results	39
4.1.	Introduction	39
4.2.	Given data and test site	39
4.2.1	. Given data	39
4.2.2	. Test site	

2	1.3.	Data ex	amination	40
2	1.4.	Implem	entation	41
	4.4.1.	Visua	al examination	42
	4.4.2.	Vario	bus trials	42
	4.4.3.	Sum	mary of parameter selection	42
2	4.5.	Result		43
2	1.6.	Summa	ry	46
5.	Valida	ation and	d analysis	47
[5.1.	Introdu	ction	47
ŗ	5.2.	Strategy	y for performance evaluation	47
	5.2.1.	Visua	al examination	47
	5.2.2.	Туре	I, Type II and Type III error	47
5	5.3.	Parame	ters for removing wall and vegetation points	49
	5.3.1.	Para	meters setting for detecting wall	49
	5.3	.1.1.	Sample 1: low density of points on the wall	49
	5.3	.1.2.	Sample 2: high density of points on the wall	49
	5.3.2.	Para	meters setting for detecting vegetation	50
	5.3	.2.1.	Sample 1: dense forest	51
	5.3	.2.2.	Sample 2: vegetation in open area	51
	5.3	.2.3.	Sample 3: low vegetation	52
5	5.4.	Sensitiv	ity of filtering parameters	52
	5.4.1.	Maxi	mum distance to surface	52
	5.4.2.	Para	meter optimization in classifying single tile	53
ŗ	5.5.	Analysis	s of Optimum Result	54
ŗ	5.6.	Influenc	ce of dividing	55
	5.6.1.	Impa	ct of overlap	55
	5.6.2.	Impa	ct of tile size	56
ŗ	5.7.	Analysis	s of time consuming	56
ŗ	5.8.	Summa	ry	57
6.	Concl	usion ar	nd further work	59
6	5.1.	Conclus	ions	59
6	5.2.	Recomr	nendations	60
7.	Bibilio	ography		61
Ар	pendix -	– A		63

List of figures

Figure 1-1: Illustration of DSM, DTM and nDSM	1
Figure 2-1: Relationship between horizontal distance and Δh in structure element	6
Figure 2-2: Classification result of terrain and off-terrain points using structure element	6
Figure 2-3: Determination of candidate point using adaptive TIN models (Axelsson, 2000)	7
Figure 2-4: Weight function (source: Kraus and Pfeifer 1998)	8
Figure 2-5: Segmentation/cluster (Sithole and Vosselman, 2003)	8
Figure 2-6: 2D Hough transform (Vosselman et al., 2004)	9
Figure 2-7: Scan line segmentation (Sithole and Vosselman 2005)	10
Figure 2-8: Transmitted and received signals in a wooded area with a small-footprint	11
Figure 2-9: Crossing-border line	13
Figure 2-10: Pre-classified of lines	13
Figure 3-1: Overview of methodology	15
Figure 3-2: Workflow of preprocessing	16
Figure 3-3: Photogrammetric overlap (Columbia, 2009)	16
Figure 3-4: Dividing datasets with overlap	17
Figure 3-5: Comparison of the two segmentation algorithms result.	18
Figure 3-6: Sample of coding unique segment number	19
Figure 3-7: Frame workflow	20
Figure 3-8: (a) Spatial arrangement of segments (b) Topological description of this region	21
Figure 3-9: Detecting adjacent segments	23
Figure 3-10: Boundary zone between segment S1 and S2	24
Figure 3-11: Range of boundary zone in connected segments	24
Figure 3-12: Range of boundary zone in segments with gap	25
Figure 3-13: Measuring height difference in profile view	25
Figure 3-14: Discontinuities scenarios at a neighborhood (Nirodha Perera, 2007)	26
Figure 3-15: Topological description including height difference	26
Figure 3-16: Profiles of complex objects	27
Figure 3-17: Topological description of profiles in Figure 3-16	28
Figure 3-18: Topological description with removing object segments	29
Figure 3-19: Rules for classification	30
Figure 3-20: Profiles of adjacent tiles	31
Figure 3-21: Sub-classification segments based on location	32
Figure 3-22: Combination segment in adjacent tiles	34
Figure 3-23: Detecting all corresponding parts	34
Figure 3-24: Parameters involved in the workflow	37
Figure 4-1:FLI-MAP 400 system (Fugro, 2007)	39
Figure 4-2: Orthoimage of test site (source: Fugro)	40
Figure 4-3: Height range from planer surface	40
Figure 4-4: Distribution pattern in horizontal view	41
Figure 4-5: Result of preprocessing (before and after processing)	43

Figure 4-6: Classification result in one tile	. 44
Figure 4-7: Identify object from combination segment	. 44
Figure 4-8: Identify terrain from combination segment	. 45
Figure 4-9: DTM result	. 46
Figure 5-1: Type I error in extracting low density of wall points	. 49
Figure 5-2: Type I error in extracting high density of wall points	. 50
Figure 5-3: Sample 1: high dense forest	. 51
Figure 5-4: Sample 2: vegetation in open area	. 51
Figure 5-5: Sample 3: low vegetation	. 52
Figure 5-6: Sensitivity of maximum distance to surface	. 53
Figure 5-7: Sensitivity of ratio	. 54
Figure 5-8: Test site and error	. 55
Figure 5-9: Effect of buffer width	. 55
Figure 5-10: Impact of tile size	. 56
Figure 5-11: Unclassified courtyard in small tile size	. 56

List of tables

Table 3-1: Filtering assumptions	19
Table 3-2: different cases in filtering	
Table 3-3: different confidence level for segments in one tile	
Table 3-4: Parameters and their description	36
Table 4-1: Value for parameters	41
Table 5-1: Cross-matrix table (Sithole and Vosselman, 2004)	48
Table 5-2: Table of error type (Nirodha Perera, 2007)	48
Table 5-3: Variable setting for Tolerance angle – low density points on wall	49
Table 5-4: Variable setting for Tolerance angle – high density points on wall	50
Table 5-5: Variable set for filtering parameter optimization	53
Table 5-6: Summary of classification result	54

1. Introduction

1.1. Digital Terrain Model

Nowadays, airborne laser scanning (ALS) system provides accurate surface points which have been a preferred data source for topographic mapping. The raw points acquired by ALS can be used for reconstructing the top surface known as Digital Surface Model (DSM) (Lee and Schenk, 2001). The surface which DSM represents includes roof, vegetation and terrain. Since the active sensor of ALS is line-of-sight equipment, most region of DSM is considered as 2.5D model.

In many projects, such as urban planning, water conservancy and geologic hazard assessment, engineers prefer Digital Terrain Model (DTM) to DSM. DTM can be described as a continuous topographic model of the bare earth and can be manipulated by computer programs. In this research, DTM and digital elevation model (DEM) are interchangeable. The terrain or elevation defined here as boundary surface between the solid ground and atmosphere.

Normalized DSM (nDSM) is the height difference of a DSM and DTM. Hence, nDSM(x,y) = DSM(x,y) - DTM(x,y). In some cases, DTM(x,y) need to be interpolate from its surrounding to calculate nDSM. Figure 1-1 illustrates the relationship among DSM, DTM and nDSM.



Figure 1-1: Illustration of DSM, DTM and nDSM

In this research, ALS point which is distributed on the surface of bare earth is called as terrain point, whereas point on the object surface is named as object point.

1.2. Motivation and problem statement

Knowledge of geometric characteristics of terrain can be used for many applications. By using the acquired terrain model, engineers or planners can apply coastal zone management, water management, insurance, avalanche risk assessment, etc.

DTM can be derived by the techniques of field survey, photogrammetry, InSAR and ALS. Compared to the traditional photogrammetric method to derive DTM, ALS is a range measurement system. By

integrating with the Global Positioning system (GPS) and Inertial Navigation System (INS), point clouds contain the information of 3D coordinate (x, y and z). Since ALS is an active survey technique, the obtained point clouds are independent with the sun position and atmosphere windows. The most significant pro of ALS is the higher accuracy (3-7cm) compared to others (Nirodha Perera, 2007). Furthermore, ALS provides a reliable and cost-effective surface of landscape.

However, as described in section 1.1, the raw data of laser scanning are the points distributed on the surface of the landscape and can be directly used to generate DSM instead of DTM. DTM can be obtained by classifying and removing off-terrain points from DSM. The algorithms for removal of such points are called filtering.

The derivation of DTM is one of the main applications of ALS. Many algorithms have been developed for filtering. Some approaches establish a structure element which describe admissible height difference that depend on horizontal difference (Vosselman, 2000). While some approaches use seed points to establish triangulation and detect the points in the triangulation based on height difference (Axelsson, 2000). Further, surface-based filters assign different weights for each point and interpolate the terrain trend (Kraus and Pfeifer, 1998). However, all of the above approaches only cover the local neighborhood without topological and geometric consideration. The result of this type of point-wise filter algorithm cannot provide reliable result. Segment-based filter algorithm, on the other hand, provides global looking approach for the point clouds. The processing of LiDAR data can be strengthened by first aggregation points and then analyzing segments rather than individual points (Filin and Pfeifer, 2006). Segmentation can provide more reliable result since geometric and topological information are considered in the step of classification (Vosselman, 2009).

However, segmentation performed in large area arise a problem of handling the huge amount of points in one go in computer's physical memory. As the development of laser scanning sensor, the measurement frequency of the sensor is up to several hundred kHz and it made high point densities of more than twenty points per square meter. The high point density leads to better accurate DTM but due to limited size of computer memory, it is an impossible to perform segmentation or classification processing in one go in computer memory. The current approaches for solving this obstacle are either using hierarchical approach or deconstructing the whole datasets into several tiles. (Pfeifer et al., 2001) use robust adjustment method with a hierarchical approach. However, this hierarchical approach is only suitable for point-based filtering and relatively large amount of point. By using hierarchical approach, points are reduced to low density and increase the distance between adjacent points. In order to cluster the reduced points, more tolerance segmentation parameters should be set. Then the result of segmentation may still have problem.

1.3. Research identification

1.3.1. Research objectives

Based on the problem for hieratical approach that is not suitable for large research area, the main objective of this research is to design a splitting and combination algorithm for huge datasets to filter

DTM. The algorithm is splitting the whole block of datasets into small tiles and filtering based on the segment-based approach. Then based on the classification result, another classification approach of using information from multiple tiles is developed to derivation DTM.

The purpose of the algorithm is to remove all the object points and reserve bare earth points from large amount of LiDAR data.

1.3.2. Research questions

For solving this research problem, several research questions need to be answered:

- 1) How to achieve accurate segments?
- 2) How does the classification algorithm work?
- 3) Which algorithm can be used for detecting the incomplete segments which are shared by multiple tiles?
- 4) How to classify combination segments?
- 5) What is the relation between tile size and quality of DTM extraction?

1.4. Innovation aimed at

The innovations in this study are:

- Design a new approach to detect different parts of combination segment in tiles.
- Classification of the combination segments.

1.5. Structure of thesis

To fulfill the objective and questions mentioned above, this thesis is divided into seven chapters.

Chapter 1 – Introduction

Introduction of DTM, problem remain, objectives and research questions are described.

Chapter 2 – Review of literature

Review of related techniques in the literature which have been used for DTM extraction and combination tiles as a whole.

Chapter 3 – Proposed method

A new strategy and methodology of filtering huge ALS data is described. There is a particular description for the new strategy of splitting and combination for the data.

Chapter 4 – Implementation and result

This chapter describes the testing datasets and the characteristics of the testing area. And then, for each step, parameter selection and result are discussed. The final result is achieved at the end of this chapter.

Chapter 5 – Validation and analysis

The chapter dedicated to the quality analysis of the final result. For each step, the parameter sensitivity is discussed.

Chapter 6 – Conclusion and Future work

This chapter provides the conclusions of this research and gives some further recommendations for improvement.

Chapter 7 – Bibliography

2. Review of literature

2.1. Introduction

Due to the accuracy potential of the laser scanning system, LiDAR is more suitable for DTM generation and break-line extraction. However, to guarantee the accuracy of DTM, filter algorithm is a crucial element. The purpose of filtering is to remove off-terrain points. Among these filtering algorithms, one common characteristic is that they all use height discontinuities to classify points but use different approaches to measure discontinuities. An overview of current algorithms is presented in section 2.2.

However, all the current algorithms mainly deal with a small size of LiDAR data. Since there are limited researches on dividing and combination ALS data have been done, a similar method of scanning part of big paper map and then combining them as a whole digital map is discussed in section 2.3. According to the objective is to filtering huge amount of ALS points, a summary of all the existing algorithms to perform huge datasets are discussed in section 2.4.

2.2. Terrain points extraction

Extracting terrain points from laser scanning data has been developed by many researches. All the methods evaluate the height different between the target and its neighborhoods to detect discontinuities. The target can be single point or a cluster of points. Thus, the approaches can be categorized filtering as Morphological, Surface-based and Segment-based filter.

2.2.1. Morphological filter

Morphological filter is also known as sloped based filter. The major assumption of these algorithms is that terrain has a certain maximum slope (Sithole and Vosselman, 2003). The filter is based on the planimetric distance and height difference. Morphological filter has the relationship with mathematical morphology (Vosselman, 2000). In mathematical morphology, erosion operation is used for designing a structure element $\Delta h_{\max}(d)$ which describes the admissible height differences as a function of the planimetric distance d. The distance d is the horizontal distance. Thus, distance between p_1 and p_2 is $d(p_1, p_2) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$. The larger the distances between a ground point and its neighboring point, the larger the height difference accepted between them (Figure 2-1). The structure element is placed at each candidate point and this point is identified as terrain point if no height differences to its neighbors are above the admissible height difference. Thus, the set of ground points can be defined by $DTM = \{p_i \in P | z_{p_i} \leq e_{p_i}\}$. The term z_{p_i} is the height of point p_i and e_{p_i} stands for the eroded value at p_i . Definition the range of neighbors of point p_i can be done by determination the maximum planimetric distance d_{\max} . The Figure 2-2 shows the classification result of the points. The points with black are classified as terrain points as there is no

point under the structure element. And with the same reason, the points which classified as off-terrain points appear white color.



Figure 2-1: Relationship between horizontal distance and ∆h in structure element



Figure 2-2: Classification result of terrain and off-terrain points using structure element

Some extensions and variants of morphological filters focus on the shape of structure element. Sithole described an adaptive slope based filter with a rotationally symmetric structure element(Sithole, 2001). This method is the adaptive filter developed by (Vosselman, 2000). By admitting more height differences for the steep areas, the performance of this algorithm is improved in steep slopes.

In spite of single structure element shape, (Kilian et al., 1996) and (Zhang et al., 2003) develop filtering methods with multiple structure elements. For this variant, the approximated ground surface should be acquired first. The approximated ground surface can be acquired by morphological opening operation. Then, the optimal size of structure elements are defined depend on the size of object. The certain weights are assigned to the points depending on structure element size. Finally, points with high weight are classified as terrain points and others are removed.

2.2.2. Surface-based filter

These algorithms use a parametric ground surface with certain buffer to detect whether the point located above or below the surface. Then the classification can be made based on the position of points.

(Axelsson, 2000) utilize the lowest points in large grid cells spreading located at corners as terrain points. Triangular Irregular Network (TIN) is built based on these seed points in order to form reference surfaces. And then, all the points above the reference surface are classified by investigating the offsets of the non-classified points. The offset are the angles between triangle face and the edges from the triangle vertices to the new point.

From the Figure 2-3, p_1 , p_2 and p_3 are seed terrain points and the triangle with these three points as the triangle vertices is considered as reference surface. A new point p_c is determined using this reference surface due to the vertical project of p_c is inside of the triangle. The offsets between the reference surface and p_c are α_1 , α_2 and α_3 . If all of the offsets below the threshold value, the point p_c is classified as a terrain point.



Figure 2-3: Determination of candidate point using adaptive TIN models (Axelsson, 2000)

(Kraus and Pfeifer, 1998) expressed an algorithm based on linear prediction but an individual accuracy for each point unit. Initially, the parametric plane surface generated by averaging Z value of all the terrain points and object points. The surface assigns the same weight for all points. The points above the surface have positive residuals, whereas points such as terrain points have negative residuals. The residuals are used to compute each weight for the points. The weight function can be seen in following figure.



Figure 2-4: Weight function (source: Kraus and Pfeifer 1998)

Utilizing the histogram of residual, the shift value g (Figure 2-4) can be defined and the point with the residual less than g is assigned the weight as 1. For the point with the residual more than g+w is with weight 0. Due to the higher weight has higher influence on the run of surface, the weight can be used for deriving iterative surface.

There is a variant method done by (Pfeifer et al., 2001). In the work, robust adjustment method includes a hierarchical approach to classify object points and reduce running time. The derived DTM from coarse resolution is used to pre-select probable terrain point for the finer resolution.

2.2.3. Segment-based filter

Segment-based filter combines two parts. The first one is segmentation algorithm and the other one is filtering based on the generated segments.

Segmentation can be defined as aggregating and clustering points with similar feature(Filin and Pfeifer, 2006). Segmentation method is obtained to get a higher level of information from the points in a point cloud. In regard of this conception, the processing of LiDAR point clouds can be strengthened to analyze segments rather than individual laser points. Every point in the same segment should belong to the same class. Then the rational behind of such algorithms is to use contextual and geometric information to classify points. Figure 2-5 shows the segmented points appear red color and non-segmented points show black.



Figure 2-5: Segmentation/cluster (Sithole and Vosselman, 2003)

With assumption that all points in a segment have the same class type, filtering of point clouds can be deemed as filtering segments. The accuracy of segmentation is one of the most important elements for the quality of filtering. Planar and smooth segmentation is the two domain segmentation algorithms. The two segmentation algorithms firstly define a seed surface. The seed surface is determined by using 3D Hough transform algorithm (Vosselman et al., 2004). Stipulated in Equation 2-1 is a mathematical description of 3D Hough transformation.

 $d = \sin \alpha \cdot \sin \beta \cdot X + \sin \alpha \cdot \cos \beta \cdot Y + \cos \beta \cdot Z$ (Equation 2-1)

Where:

<i>d</i> :	Height of the surface at the origin $(0,0,0)$.
lpha and eta :	Slope of the plane along the X- and Y-axis.

Parameter space is defined by the three parameters ($d \ \alpha$ and β). The planes for each point in object space can be represented as a curve in parameter space. The parameter in Equation 2-1 is determined by the position in the parameter space where most planes intersect. For easily visualization, parameter space in following Figure 2-6 only uses the parameter d and α .



Figure 2-6: 2D Hough transform (Vosselman et al., 2004)

After detecting seed plane, the set of seed points in this plane are used to cluster the adjacent nonclassified points to the segment. The difference between the two segmentation algorithms is the way they detect the surface of a candidate point. Planar segmentation add points if the candidate point is below the threshold distance to the seed plane and smooth segmentation measure the distance between candidate point and its locally defined smooth surface (Vosselman, 2009).

(Nardinocchi et al., 2003) use surface growing technique for segmentation in grid data. Surface growing in this method is performed by comparing the height difference between seed point and its eight connected neighbors. If the height difference is below the threshold value, the surface grows this region. The process runs on until surfaces cover all points in the region. The border between the surfaces has discontinuities more than the threshold. The information of adjacent segment number and height different information can be reserved by the border. The information of segment size and segment number can be kept by the segment itself. Then a geometric and topological description can be made. Based on the characteristics of different landscape, the classification achieved by all the information mentioned above.

The method by (Sithole, 2004) has assumption that points in the same segment can connect each other. This sense of connection would possible as the road connect two positions when they have similar height. By this rational, segmentation is performed along multiple oriented lines. The height differences and horizontal distance difference are used for detecting connection for each line (Figure 2-7 (b)). For each direction of scan line, the profiles with line connection are created. And by overlaying of profiles, two disconnected segments emerge (Figure 2-7 (c)). Figure 2-7 (a) is the landscape. From the figure, the black segment is enclosed by white segment and the black segment has higher altitude than its surrounding. Thus, the black segment can be classified as object segment.



Figure 2-7: Scan line segmentation (Sithole and Vosselman 2005)

(Tóvári and Pfeifer, 2005) use raw point clouds for surface growing. The segmentation algorithms utilize the estimation of normal vectors of triangular plane. By setting acceptance difference with adjacent normal vectors, the segment is obtained with minimum size. Then, instead of computing residual for each point (Kraus and Pfeifer, 1998), the residuals are represented for each segment. And depending on the residual, all points in the segment are assigned the same weight.

2.2.4. Full-waveform exploitation

In order to improve filtering results, the characteristics of full-waveform are used for classification. Full-waveform ALS system is able to record the full waveform of the backscattered echo(Mallet and Bretar, 2009). Because laser beam can penetrate vegetation canopies, more spatial information in vertical dimension can be obtained. Benefitted by acquiring more terrain points in forest area, DTM generated by multiple echoes system provide more quality than single echo device. Figure 2-8 shows an accurate altimetry description within the laser footprint.



Figure 2-8: Transmitted and received signals in a wooded area with a small-footprint (Mallet and Bretar, 2009)

To estimate whether the ground has been reached, (Doneus et al., 2008) use the echo width and amplitude to exclude echoes, which are not reflected from ground. Investigating the echo width can improve classification of ALS data into terrain and off-terrain points at low vegetation. Then DTM generated by robust interpolation which assigns less weight to the points with wide echoes.

2.2.5. Comparison current filtering algorithms

All the current filtering algorithms classify the terrain and off-terrain points based on detecting discontinuities. The assumption is that object has higher altitude than Bare Earth. Objects break the continuity of the terrain.

The remarkably difference among these filtering algorithms is the input data. Some of the algorithm use rasterized data for processing. The advantage for this type of data is that it can use the digital image tools and with high efficiency. However, rasterized data is just 2.5D and have relatively low resolution. The result is in a loss in precision in comparison of using point clouds (Axelsson, 1999).

Another difference of these filtering algorithms is how they assume the Bare Earth:

Morphological filter – For these algorithms, the Bare Earth has its maximum slope in certain horizontal distance. If the candidate point has a slope more than the defined maximum slope, this point will belong to off-terrain points.

Surface-based filter – By these algorithms, Bare Earth can be described as a parametric surface with a corresponding buffer zone. The points below this parametric surface are accepted as terrain points and have higher influence on the run of surface.

Segment-based filter – In this case, Bare Earth segment can be obtained by surface growing. Object segment can be classified when this segment is above its surroundings (i.e. the object segment is discontinuous).

A comparison of filter algorithms was published by (Sithole and Vosselman, 2003). Even if the quality of DTM mainly depends on parameter settings, the assumptions of algorithms also affect the result. Based on the bare earth assumption, morphology filters can hardly keep balance between steep slopes on the bare earth and off-terrain points in flat terrain. Surface-based filters, on the other hand, consider the surface trend. However, the iterative ground surface obtained by terrain interpolation. During interpolation procedure, more parameters are involved for each pass. Segment-based filters have the advantage that the segments represent man-made object like roofs and cars. Segmentation method is obtained to get a higher level of information from the points in a point cloud. Information obtained is usually the knowledge of the extent of homogenous regions in a landscape and these homogeneous regions are good indications of the contents of the bare earth.

2.3. Technique of combination images

All these developed filtering performed in relatively small site. The size of the test site is suitable for applying filtering algorithm in one go in computer memory. The whole block of raw ALS data can also be divided into tiles with suitable size and applies segment-based filtering. However, the classified segments which are intersecting the edge of tile are with low classification result. These segments which shared by multiple tiles are named as incomplete segment. In order to find all context of incomplete segment, the most important step is to detect the incomplete segment in each tile and find their corresponding parts from multiple tiles.

(Wang and Zhao, 1994) proposed the method to automatically detect and combine lines in vectorized maps. Due to the technical limitations at that time, the only way to generate large area of vectorized map from paper map is to scan part of the paper map at one time. Then all the digitized files are combined to a complete vectorized map. They first divided the large paper map into several tiles by rows and columns. For each tile, there is a vectorized files generated after scanning. As they argued that point can be recognized as the shortest line and polygon is an enclosed line, all the elements of the map is transformed to line and recognized from each tile.

When separating the paper map, every tile and its neighbors have an overlap area in between (i.e. the lines inside of the overlap area is recognized at least twice). Figure 2-9 shows the four adjacent maps. And the gray areas present the overlap areas. The overlap area is used to combine the two adjacent tiles. In the same figure, line AB in tile 1 and tile 2 is separated to two parts (i.e. line A and line B). The section of line AB in overlap area is recognized twice. Via this information, determination can be made whether the two individual lines from different tiles belong to the same line. Some of

the line like CEFD crosses tile 1 and tile 3. Line EF is recognized in tile 1 and the line is completely in overlap area. Line CEFD in tile 3 can be recognized totally, therefore there is no need to combine this line.



Figure 2-9: Crossing-border line

All the lines in individual tiles can be pre-classified as crossing-border line and non crossing-border line. The line 5 in Figure 2-10 does not cross the border but others do. Even for the crossing-border lines, the direction the line crossed can also be used for sub-classification. For example, the line 3 only cross the right bounder and some of the lines can cross two borders like line 1, 2, 4.



Figure 2-10: Pre-classified of lines

During combination step, the most important item is to detect the corresponding lines. It is defined that the distance between two points is the sum of the absolute value of x difference and y difference. Then the distance between two lines in the overlap area is the sum of the distance between corresponding pair of points in each line. If the distance between two line is small, then it illustrate that the two line have high correlation.

In this research, segment instead of line as the basic element should be combined from multiple tiles. A research also focuses on the combination of LiDAR segments(Lee and Schenk, 2002). Two segments are to be considered with high correlation if there is significant proof that they share the similar surface parameters and roughness. The conception to detect correlation is that the two segments are put in object space and detect whether they can be merged or not. The merging confidence shows

the degree of confidence in merging two segments. The merging confidence between two segments S1 and S2 is defined as:

$$\boldsymbol{\theta}_{merge}(S_1, S_2) = \boldsymbol{\theta}_{merge}(S_1 \leftarrow S_2) \cdot \boldsymbol{\theta}_{merge}(S_2 \leftarrow S_1)$$

Where $\theta_{merge}(S_1, S_2)$ is the merging confidence between S1 and S2; $\theta_{merge}(S_1 \leftarrow S_2)$ is the confidence in merging S2 into S1; $\theta_{merge}(S_2 \leftarrow S_1)$ is the confidence in merging S1 into S2. $\theta_{merge}(S_2 \leftarrow S_1)$ is the measure of probability of points in S1 have the similar surface parameters with S2.

2.4. Summary

The comparison of filtering illustrate that segment-based approach provide precise result and is able to deal with terrain segments with discontinuities. According to this main objective of handling huge size of raw LiDAR points for filtering, the whole block is decomposed to several tiles. If point-wise filtering is applied in each tile, it is should be ensured that each tile should have terrain points. Due to no combination information, point-wise filtering can not use the information from multiple tiles.

Based on the analysis above, in order to extract precise DTM from huge ALS data, segment-based filter should be applied. Segments as the elements are used to complete the combination segment. In this research, a new segment-based approach for DTM derivation in ALS data is represented in chapter 3.

3. **Proposed method**

3.1. Introduction

To achieve the objectives of this research, the methodology is divided into four major sections in this chapter. The preprocessing is introduced in section 3.2. The strategy of filtering algorithm is discussed in section 3.3. Detection and classification of combination segment from multiple tiles are introduced in section 3.4 and an approach of merging all tiles is given in section 3.5. A summary of this algorithm is described in section 3.6. The overview of this chapter can be illustrated in following figure.



Figure 3-1: Overview of methodology

3.2. Preprocessing

Preprocessing as the foremost step is to prepare input data. As filtering works on segment, accurate segments are generated in this step. As illustrated from the Figure 3-2, preprocessing begins with splitting the whole block of datasets into tiles. In order to obtain accurate segment, the second step is to remove wall and vegetation points. After removing wall and vegetation points, accurate segment can be achieved by smooth segmentation. At last, all the segments are assigned a unique segment number.



3.2.1. Dividing datasets

ALS covers a wide range of areas with point information of x, y and z and due to huge size of point cloud the computer memory is not able to process these data. Therefore, the approach in this research is to first divide the study area into equal sub-areas in the form of "tiles". The division of these sub-areas is similar to aerial photographic tiling. Figure 3-3 shows an example of tilling in aerial photograph.



Figure 3-3: Photogrammetric overlap (Columbia, 2009)

The process of splitting the whole area into small tiles can be deemed as the process of acquiring aerial photos. The range of a tile is similar with a range of single image in triangulation. The whole block of point clouds are divided into several tiles with similar size in rows and columns that are

based on the coordinate information of x and y in 2D. And the size of each tile depends on the size of the computer memory in use.

When dividing tiles, a buffer area is assigned automatically. The buffer area is similar to aerial photos overlap. There are two major reasons for adding buffer area, the first reason is that buffer area provides more contextual information and the second reason is that buffer area can be used for complete segment from other tiles. Figure 3-4 illustrates a simple splitting procedure which shows the whole datasets being separated into four tiles. The striped area represents the overlap portions and the width of overlap is two times than a single buffer area since it takes into account another buffer area of an adjacent side.



Figure 3-4: Dividing datasets with overlap

3.2.2. Removing wall and vegetation points

The Segment-wise approach filters point based on segment. The segment-wise filtering assumes that all the points in one segment should belong to the same class. Thus accuracy of clustering points with same class is the essential element for the accuracy of final result. If directly applying segmentation, some vegetation points closed to Bare Earth are grouped in terrain segment. Some points on the wall connect the terrain and roof points. Wall points act as glue to merge terrain and roof segment to form a single segment in merging step. The strategy of merging step is introduced in section 3.3.3.

In reality, wall and vegetation points in landscape are points distribute on wall surface (named as wall points) and crown of vegetation surface (named as vegetation points). In order to guarantee the segmentation result, wall and vegetation points should be analyzed and removed before segmentation.

The characteristic of wall points is that they can be identified in a cluster using planar segmentation. The walls of a building always appear as vertical plane in the point cloud whereas terrain segment can not be as vertical plane. With this attribute, point clouds are firstly applied planar segmentation and the whole data segmented. For each segment, a plane is fitted by using least square method for estimating plane parameters. A process is performed to check whether the plane is vertical. All the segments with vertical planes are classified as noisy and removed from the point cloud. Vegetation also affects the accuracy of segment. Vegetation points can be segmented into terrain segment when they are closed to terrain. Furthermore, too many generated segments in vegetated area reduce the efficiency and the result of filtering. In order to remove the segmented vegetation points, pulse type proposed by (Doneus et al., 2008) is used. It is assumed that the points on the terrain, roof and wall are most likely the last echo of pulse. Though points on the edges of roof are not last echo, the amount of this kind of points is relatively small comparing the size of segment. In contrast, vegetation segment contains many not-last echo points. The component percentage of not-last echo points toward the whole segment size can be used for detecting vegetation segment. The step of detecting vegetation segments is at the same time of detecting wall after planar segmentation.

3.2.3. Smooth segmentation

The advantage of planar segmentation is that most of man-made objects like roofs and cars can be detected as a set of planar surfaces. However the terrain is considered as a smooth, continuously changing surface. Then the advantage of smooth segmentation is that this segmentation algorithm can represent the character of terrain.



Figure 3-5: Comparison of the two segmentation algorithms result. (a) Point clouds with color coded heights, (b) Point cloud segmented into planar surfaces, (c) Point cloud segmented into smooth surfaces.

The result of planar segmentation (Figure 3-5 (b)) shows roof planes composed by several segments and terrain is divided into multiple segments. Vegetation with its complex shape is clustered into many small segments. White points are non-segmented point as they do not reach the minimum threshold of the number of points to generate a segment. This result leads to many segments and difficult to describe their context.

The appearance of smooth segments (Figure 3-5 (c)) illustrates that segments on one roof are grouped as one segment (compared to planar segmentation). The terrain with connected points is also grouped as one segment. Without the affect of wall and vegetation points, the accuracy of segmentation is improved and the amount of segments reduced. Another advantage of smooth segmentation is that it accelerates the performance of filtering in each tile because of limited number of segment. Furthermore, the smooth segmentation parameters are also used to detect corresponding segments from different tiles in section 3.4.2.

In order to maintain smooth and continuously changing surfaces in one segment, smooth segmentation instead of planar segmentation should be used after removing wall and vegetation points. In this research, segmentation algorithms only consider the spatial pattern of ALS points.

3.2.4. Unique segment number

Smooth segmentation algorithm produces a list of segments. Due to datasets have been divided into several tiles, it is necessary to uniquely identify every segment in all tiles. In this research, after smooth segmentation, segments in each tile are assigned a unique number. In order to distinguish individual segments in different tiles, the information of rows and columns where the tile occurs within the block is integrated to encode the segment. For example, if a segment in row 2 column 1 has the initial segment number 19, then the segment number for this segment can be transformed to 0201019 where 02 is the row code and 01 is the column code in Figure 3-6. The purpose of encoding is to assign all segments with unique segment number.



Figure 3-6: Sample of coding unique segment number

3.3. Classification in one tile

Classification in each tile is an important part for filtering the whole datasets. The filter works to classify segment in each tile is based on the assumption of different attribute between terrain and object. Different assumptions result in different filtering algorithms and their performance have been described in chapter 2. These assumptions can be sorted into three categories: geometric assumption, topological assumption and Discontinuities assumption, which are all based on segment.

Coomotric	1) All points in a segment belong to same class	
assumption	 The space area of Bare Earth segment is larger than the biggest object segment 	
	3) Topological information of segment can be obtained by	
Topological	investigating neighbor points	
assumption	4) Object segments are separated by significant height jump	
Discontinuous	5) Object segment has higher altitude than its surrounding	
assumption	6) Gradients in the Bare Earth have the maximum slope threshold	
	which is less than the gradients of discontinuities	

Since the complex landscape, it is impossible to utilize single assumption to satisfy every landscape situation. Thus, in this research, all assumptions are used to design this filtering.

3.3.1. Designing filter framework

Based on these assumptions, Figure 3-7 illustrates the mechanism of the filter frame workflow.



Figure 3-7: Frame workflow

The input data for filtering are segments which are the output of preprocessing. Since segments are not only used for classification in one tile but also used for utilizing information from multiple tiles (section 3.4.), segmentation procedure has been incorporated in pre-processing phase. The concept of segmentation is based on the geometric assumption described in Table 3-1.

The filtering consists of seven steps:

Step 1: All the points should find their neighbors in 2D. The radius of finding neighbor points is changed in each pass.

Step 2: Topological description about spatial arrangement of segments is built in this step.

Step 3: For the adjacent segments, a comparison of height difference is done by using their boundary zone.

Step 4: After measuring height jump between segments, all segments can be categorized as different cases. Some cases of segment can be classified directly by using topological and geometrical information.

Step 5: Based on the classification result of Step 4, the topological description can be rebuilt by removing all object points and merging the adjacent segment with similar altitude.

Step 6: If there are still some segments which are not classified, it means that the candidate segment does not have contextual information of neighbor. Then, finding radius in step 1 should be increased for next iteration.

Step 7: After all segments have their class, the result of classification in one tile including terrain points and object points are written to a file.

In conclusion, Step 1 and 2 can be defined as topological description and step 3, 4, 5 and 6 belongs to filtering. After each pass of filtering, topology should be rebuilt. The topological description and filtering are introduced in section 3.3.2 and 3.3.3 respectively.

3.3.2. Topological description

Since segments are created only by considering spatial distribution of points, there is no semantic information associated with them. The only way to classify terrain or non-terrain segments is by using height (z-value) of points and their spatial topology as described in topological assumptions in Table 3-1. The topology is used to describe spatial distribution of segments. Figure 3-8 (a) shows a result of the segmentation process. For example, a candidate segment S1 located in the center of a research area. By projecting all points into a planar surface and investigating the 2D neighborhood segments, segment S1 is adjacent to S2, S3 and S4, and spatial arrangement can be described in Figure 3-8 (b), where the line between two segments stands for direct connectedness (or even overlap).



Figure 3-8: (a) Spatial arrangement of segments (b) Topological description of this region
Step 1: Finding neighbor points

In order to get topological description, the first thing to know is the neighbors from the selected point. There are two efficient methods for finding neighbors of a given point (Rabbani Shah, 2006).

- K nearest neighbors (KNN) is used to select points of an area of interest (AOI). When the number of neighboring points is fixed, all the points in point cloud are compute the Euclidean, Manhattan, or any other distance between the selected point and candidate point. Only a defined number of points within the nearest distance are accepted as neighbors of the selected point.
- Fixed distance neighbors (FDN) define the maximum distance between selected point and candidate point instead of define the number of neighbors. All the points inside AOI are accepted as neighbors.

Detecting neighbors by using KNN method has the problem in selecting the number of neighbors. Due to overlap in different strips and altitude variability in landscape, point clouds do not obey the uniform distribution. The AOI in high point density area is small when compared to low density areas. And also, if two adjacent segments are with large gap in between, it is difficult to find neighbors from the adjacent segment. In order to find contextual information, the better way is to fix the value of AOI. Then, FDN is selected to detect neighbors from selected point. As the topological description is based on 2D, the range of finding neighbors should also be considered in 2D. In this research, the range to find neighbor points is named as finding radius.

Step 2: Finding neighbor segment

After finding neighbors for all points, the next step is to detect contextual information from selected segment. The context here can be defined as the adjacent or overlap segments from the selected segment in 2D. The Algorithm 3.1 represents how to obtain the adjacent segment number from candidate segment S1:

Algorithm 3.1 - Adjacency segment
INPUT: segmented point cloud, point neighbors list, segment number list
OUTPUT: adjacent segment list
For segment number S1 in segment number list
For point P1 in point list
If P1 belong to S1
For point P2 in neighbors list of P1
If P2 not belong to S1 (P2 belong to segment number S2)
Append S2 to adjacent segment list of S1

In Algorithm 3.1, an adjacent segment list of S1 is found. Segment S1 in this algorithm is as the selected segment. From all the points in point cloud, find the points belong to S1. For each point in S1, AOI can be generated and each AOI center is located at that point. All the points inside of AOI are the neighbors of that point. Then, segment numbers are investigated for these neighbor points and

appended to adjacent segment list of S1. The list of segment number also includes S1. It should be done to exclude S1 in this adjacent segment list.

In Figure 3-9, if the AOI is totally inside of the segment, its neighbors have the same segment number as that point. Only if point locates near to the edge of the segment can find another segment point as its neighbor.



Figure 3-9: Detecting adjacent segments

3.3.3. Filtering

In section 3.2, topological description for segment spatial distribution is achieved. To classify terrain and object segment, detecting the height at boundary zone for adjacent segments and measuring height difference of them are the procedure to find discontinuities. According to topological assumption in Table 3-1 that object segments are separated by significant height jump, filtering algorithm can be perform to label the segment which has higher altitude than its context as object.

Step 3: Measurement of discontinuities

In order to measure height difference between segments, the first thing is to decide which part of segment is used to measure discontinuities. Due to discontinuities appears at the boundary of adjacent segments, it is preferred to measuring the height of boundary zone instead of the height of whole segment.

In Figure 3-10, segment S1 and S2 are the two adjacent segments. The boundary zone between these two segments is showed as S1S2. In the boundary zone, zone S12 is the boundary zone of Segment S1 to S2 while S21 is the boundary zone of S2 to S1. To detect the discontinuities of S1 and S2 is to measure height difference of S12 and S21.



Figure 3-10: Boundary zone between segment S1 and S2

The algorithm 3.2 as following describes how to create two point lists of boundary zone. The two point lists contain all the points inside the boundary zone S12 and S21 respectively.



According to the point lists, boundary zone S1S2 can be detected by radius r as finding radius. A circle with radius r is defined. The center of this circle is located at the common boundary and moves along this boundary. All the S1 points inside of this circle are appended to point list S12 and all S2 points inside of this circle are appended to point list S21.



Figure 3-11: Range of boundary zone in connected segments

When the two segments have a gap in between, S12 and S21 do not connect. S12 can be obtained by using a circle with diameter as r and this circle is tangent the boundary of S2. Thus all the points in this moving circle are belonged to list S12. S21 can also be obtained by using the same theory.



Figure 3-12: Range of boundary zone in segments with gap

As generated boundary zone of two adjacent segments, all the points inside of two boundary zone are used to measure discontinuities. Due to systematic and stochastic errors, the average height of boundary zone is used for calculating height difference.



Figure 3-13: Measuring height difference in profile view

If the difference of the mean height between two corresponding boundary regions is larger than a defined threshold, the two segments can be considered as discontinuities. The following Equation 3-1 illustrates decision of discontinuities of two segments:

 $|Mean(Z)_{s12} - Mean(Z)_{s21}| > threshold$ (Equation 3-1)

There also has situation that the difference of two segments is lower than the threshold value. The Figure 3-14 illustrates these three possible results of measuring discontinuities.



Figure 3-14: Discontinuities scenarios at a neighborhood (Nirodha Perera, 2007)

Where:

Candidate segment 1 is above the selected segment. Candidate segment 2 has similar altitude than selected segment. Candidate segment 3 is lower than selected segment.

According to assumption 6 in Table 3-1, the threshold value can be taken by investigating the Bare Earth. If the difference between these two boundary zones is smaller than the threshold value, the two adjacent segments appear with similar altitude. Then these two adjacent segments will be merged together. The merging step is described in step 5.

After measuring discontinuities of all adjacent segments, the topological description in Figure 3-8 (b) can be transformed by adding height difference information in Figure 3-15.



Figure 3-15: Topological description including height difference

Segment S1 has higher altitude than the adjacent segments S2, S3 and S4. Thus segments S2, S3 and S4 are all pointing towards S1. The same rational can be explained in segment S2 whereby it is lower than its adjacent segments. Segment S3 and S4 are also adjacent with each other, however the height different between two segments is smaller than the defined threshold value, thus the broken line is used to connect the two segments.

Step 4: Classification

According to geometric assumption 2 from Table 3-1 that the space area of Bare Earth segment is larger than the biggest object segment, the first classification can be carried out by measuring the area of the segment.

Though the point density is not uniquely distributed, the approximate amount of points per square meter can reflect the geometric area of a segment. Based on the fact that the number of points in a segment is relatively proportional to its area, the Equation 3-2 is illustrated to recognize the terrain segments.

NP > threshold (Equation 3-2)

Where: NP is the number of points in a segment. The threshold is defined by investigating the number of points in the largest object segment. Due to non-unique distribution, the threshold value should be larger than the point size of largest object segment.

Classification based on segment size has the highest priority level. For example, S5 in Figure 3-15 satisfies the Equation 3-2. Though S5 have higher altitude than S4, it is classified as terrain segment since the number of points is more than the defined threshold. It can be concluded that if the geometric area of a segment is large enough, this segment is classified as terrain without considering the topology.

After classification based on segment size, the filtering process continues and takes into account assumption 5 in Table 3-1 that object segment has higher altitude than surrounding. For example, in Figure 3-15, all the segments are lower than S1 (indicated by all arrows pointing towards S1). Therefore S1 is classified as object segment.

However, in real world, the objects have complex segment arrangement. Figure 3-16 shows the profile of complex objects which contains adjacent roof segments and Bare Earth segments.



Figure 3-16: Profiles of complex objects

In Figure 3-16, the segments S4 and S6 are classified as terrain segment firstly based on Equation 3-2. After creating adjacent segments list for all segments and measuring discontinuities, the topological description of this complex objects can be transformed to Figure 3-17.



Figure 3-17: Topological description of profiles in Figure 3-16

According to assumption 5 in Table 3-1, all the segments surrounding S1 and S4 have arrows pointing to them (i.e. S1 and S4 are higher than their contextual segments). Thus, S1 and S4 can be classified as object segment. However, S2 have higher altitude than S4 but have lower height than object S1. The segment S5 has lower height than its context. For the case of S2 and S5, it is difficult to identify and classify them.

The following list shows all possible relation cases between the candidate segment and its neighbor segments:

Case	Description	Representative key words
1	Geometric area is larger than the biggest object segment	Large segment size
2	Candidate segment is above all its context. Total _above = Total_neighbors	Above all neighbors
3	Some of neighbors and candidate segment have similar altitude	Having similar altitude with neighbor
4	Candidate segment is below some neighbors. Total_above < Total_neighbors	Below some neighbors
5	Candidate segment do not have its context	No context
6	Candidate segment is below its neighbor terrain segments	Below terrain segment

Table 3-2: different cases in filtering

Where: Total_above shows the number of candidate segment above its neighbors. Total_neighbors is the total number of its neighbor segments.

The segments with case 1 (large segment size) can be directly classified as terrain segments. The segments with case 2 (above all neighbors) can be summarized that this candidate segment has distinguish height above its context. Case 2 is suitable for assumption 5 thus all the segments with case 2 are classified as object segment.

Case 6 (below terrain segment) usually occurs when the terrain has a depression. In this research, the depression in terrain is also classified as the terrain.

Step 5: Rebuilding topological description

However, due to the complex object segment arrangement, filtering need an iterative step to classify all segments. After each iterative process, object segments are removed. Then topological information is rebuilt for all remaining segments. In some cases, case 4 can be transformed to case 2 (above all neighbors). For example, in Figure 3-17, the segments S1 and S3 is suitable for case 2 and can be firstly classified as object segment. In next iteration, all points in S1 and S3 will not be considered for creating topology. Then topological description appears as in Figure 3-18:



Figure 3-18: Topological description with removing object segments

The segment S2 as previous point cloud belongs to cases 4 (below some neighbors), whereas S2 with reduced point cloud belong to case2 and can be classified as object segment.

If two adjacent segments have similar altitude, these segments belong to case3 (having similar altitude with neighbor). This situation happens when two segments touch or have same altitude level with each other. Then these two adjacent segments will be merged for next iteration. That is the reason for removing wall and vegetation points in preprocessing. The merged segment is first tested whether it suits case 1. If not, the merged segments should have its contextual information and classified based on discontinuities.

Step 6: Increasing radius to find neighbors

Case 5 (no context) occurs when removing object segments. For example, S5 in Figure 3-18 do not have adjacent segments. This case happens when a segment is encompassed by water or vegetation. Water the same as back body absorbs all the energy from laser beam and do not returns any pulse, while vegetation is removed in pre-processing step. Courtyard segments enveloped by roof segments

also can not find context when removing object points. In this case, there is a need to enlarge AOI for finding neighbor points until different segment points are detected as neighboring points.

Step 7: Output and summary

Though detected object points are removed in each iterative of filtering, the output file should include all the terrain and object points. The reason is describe in section 3.4.

To summarize, after merging, removing object segment point or Increasing AOI, all the segments with case 3, 4 or 5 can be transformed to case 1, 2 or 3. Thus, every segment can be classified as terrain or object. The transformation can be represented as following:



Figure 3-19: Rules for classification

Where:

1) Segment changed can be described whether some segments are classified or segments are merged.

2) Increase finding Radius means increase the AOI area for finding the remote points.

In each iterative process, only object segments are removed and the iteration will not stop until all remaining segments are terrain segment or the remaining segments are the lowest segments.

3.4. Using information from multiple tiles

Though all the segments have been classified in each tile, the result of classification is not reliable for all of them. In this research, the segment which is shared by multiple tiles is named as incomplete segment and combining all corresponding parts from multiple tiles is named as combination segment. Figure 3-20 shows a special situation for the classifying result of combination segment in multiple tiles.



Figure 3-20: Profiles of adjacent tiles

The profile in real world is shown in upper middle. The profile is mainly composed by two segments S1, S2 and the segments of tree and house. Though the terrain has discontinuities in the middle of this profile, both segments (S1 and S2) can be recognized as terrain based on geometric area. However, if the profile is divided into two tiles with overlap, the result can be that in some tile the combination segment is classified as object while in other tiles the combination segment is classified as a terrain. The profile on the left shows the left tile while right illustrate right tile.

In the left tile, there is only a small part of segment S2 inside and the height jump between S1 and S2 are discontinuous. Thus S2 in left tile is above its context and classified as object segment. On the other hand, segment S2 is classified as terrain segment in right tile based on geometric area. The classification result from different tiles is not the same. For the step of merging all tiles and making DTM, it is difficult to identify the class of S2 because assumption 1 in Table 3-1 proposed all points in a segment should belong to same class.

The example mentioned above shows the unreliable classification result in individual tile. The reason is that the segment is not complete its geometric or topological information. These two items of information are used for classification. Then losing the information is result in unreliable classification.

3.4.1. Classification confidence

The segments in single tile with completeness of topology and geometry can be deemed that these segments have high confidence level of classification result. On the other hand, the segments lose their geometrical completeness or full context is considered that these segments have low

confidence level of classification result. In this research, confidences of classification have two levels: high and low level.

According to pre-processing step, the whole datasets is divided into several tiles. In order to increase context for each tiles, the buffer area is generated at the edge of the boundary. Thus, there are two boundaries for each tile. The original boundary is defined here as inner boundary and the boundary of buffer is defined as outer boundary. Depending on the location of segments, segments can be sub-classified into four cases:

Case I: The segment is totally inside of inner boundary.

Case II: The segment intersects inner boundary but lies inside of buffer area.

Case III: The segment intersects both boundaries.

Case IV: The segment is totally inside of buffer area.

The following Figure 3-21 illustrates these four cases of location. In the figure, the full line means the inner boundary and broken line stands for outer boundary.



Figure 3-21: Sub-classification segments based on location

From Figure 3-21, case I, II have complete geometry and context and their classification result should be with high confidence level. However, segments with case III lose geometric and topological information. In order to complete its topological and geometric information, the segments with case III should find all its corresponding part in multiple tiles.

Since the overlap between tiles, some segments in two (maximum four) tiles are all recognized as case II. The classification results for these segments in their tiles are all with high confidence level. As the final DTM achieved by adding all the terrain segments with high confidence level in each tile, the above mentioned segments will be added twice. The Equation 3-3 is used to assign different confidence level for these segments.

$\frac{NPIB}{NP} > \frac{1}{2}$	(Equation 3-3 a)
$\frac{NPIB}{NP} > \frac{1}{4}$	(Equation 3-3 b)

Where: *NP* is the number of points in one segment. *NPIB* is the number of points of the segment which is inside of inner boundary in one tile. If the segment is shared by two adjacent tiles and the proportion is larger than ½, this segment in this tile have high confidence level of classification result (Equation 3-3 a). Sometimes the segment is shared by 4 tiles (i.e. the segment is located at the corner of inner boundary), then ¼ is used to decide confidence level (Equation 3-3 b). Table 3-3 describes the confidence level for the four cases in one tile. There are six different types of category for all the segments in one tile.

Туре	category	confidence level	Description
1	Case I	High	$\frac{NPIB}{NP} = 1$
2	Case II with satisfy Equation 3-3	High	satisfy Equation 3-3
3	Case II without satisfy Equation 3-3	Low	Can satisfy Equation 3-3 in adjacent tile
4	Case III without satisfy Equation 3-2	Low	Lose its geometric or topological information
5	Case III with satisfy Equation 3-2	High	Geometric area has the highest priority for classification
6	Case IV	Low	$\frac{NPIB}{NP} = 0$

Table 3-3: different confidence level for segments in one tile

There are three of six types of segments which have the low confidence level. In Table 3-3, the segment which belongs to type 3 can find a corresponding segment in adjacent tile with the situation of type 2. The segment with the type 6 can also find a corresponding segment in adjacent tile with the situation of type 1. Type 5 can be classified with high confidence level since geometrical classification has the highest priority. The only remained segments are the type 4 which should be detected its corresponding parts to complete geometric and topological information.

3.4.2. Finding corresponding segments

In order to find corresponding segment efficiently, spatial distribution of tiles is used. For example, in Figure 3-22, tile 2 is adjacent and on the right of tile 1. Thus all segments in tile 1 with case III and intersect the right side of outer boundary will be detected. At the same tile, all

segments in tile 2 with case III and intersect the left side of outer boundary will also be detected. And create two lists (list 1 and list 2) to keep these segment numbers. Then select one of segments from list 1 and one of segments from list 2 and plot them in object space. To detect whether this two segment corresponds to each other is to detect whether this two segments can be merged in object space. The merging algorithm can be done by applying smooth segmentation algorithm with more tolerance parameter. After segmentation, investigating of the new generated segment with largest number of points and comparing to the whole number of points. If the number of points for the generated largest segment approximates the whole size, these two segments are assumed as corresponding parts.



Figure 3-22: Combination segment in adjacent tiles

(Equation 3-4)

The detecting corresponding segment algorithm can be described as following:

NNP/WNP > Threshold

Where: NNP is the number of points for largest new segment and WNP is the whole number of point for the two segments.

The procedure of detecting corresponding part of a segment is carried out by pair of adjacent tiles. Firstly, each pair of tiles is used for detection in row direction. This procedure only can find corresponding part in each row. After finishing detection in rows, detection in column direction is carried out. Then, with the same theory of segmentation using scan line (Vosselman et al., 2004), finding all parts of a combination segment can be achieved by overlap two profiles of detection. Figure 3-23 illustrates the processing of detecting corresponding part.





3.4.3. Classifying incomplete segment

After detecting corresponding parts, the classification procedure is carried out for these combination segments by analyzing the complete topology and geometry from multiple tiles. By investigating the classification results from each tile and finding corresponding segment from different tiles, there are the situations for these combination segments:

- All parts of the combination segment are classified as terrain.
- All parts of the combination segment are classified as object.
- Some parts of the combination segment are classified as terrain and others as object.

According to rules for classification (Figure 3-19), a segment is classified as terrain is either based on geometric area or has similar (lower) altitude toward its nearest terrain segment. Then, it can be concluded that classifying terrain segment do not need to detect all its neighbors. On the other hand, a segment is classified as object based on its full context (from assumption 5 in Table 3-1). Thus, the classification result as terrain has higher confidence level than object.

If the candidate segment in all tiles is classified as terrain, this segment will have relatively low height than its full context therefore the whole segment is classified as terrain with high confidence.

For all parts of the candidate segment are classified as object, however, it should consider its whole geometrical area firstly. In order to avoid multiple-count of the point in overlap for measuring area, the number of points for this combination segment is the sum of each portion of the part which is clipped by its inner tile boundary. If the number of points is larger than the biggest object, the candidate segment is classified as terrain. Otherwise, the segment has discontinuities higher than its context and will be classified as object segment.

As described that classification results as terrain always have the high confidence level, the combination segment with the terrain part can be directly classified as terrain segment with high confidence for all parts.

There still have the case that some parts of the combination segment are unclassified. In this case, the unclassified parts are not taken into account for classification the combination segments but the classification result is assigned to the unclassified parts.

3.5. Merging all tiles

The merging step can be carried out by each row. Due to type 1 and 2 in Table 3-2 are with high confidence level, the segments from each tile with these two cases can be firstly added to final file. Type 3 can be transformed to type 2 in another tile. Thus, this kind of sub-classification can also avoid adding duplicate points in final file. Then, the combination segments in each tile are all with high

confidence level are also be added to final file. Since there are overlaps among corresponding segment, the combination segment should be clipped by inner boundary of its tile before the adding step.

3.6. Summary of the algorithm

This algorithm is executed by firstly applying filtering for each tile, and then two confidence levels are assigned for all segments in each tile. For the segments with low confidence, they should be considered in multiple tiles. The combination segment with completeness of topology and geometry can be classified with high confidence level. Thus the final DTM file can be achieved by investigating all tiles and extract the terrain segments.

To implement the algorithm, different input parameters are presented. Some values of the parameters are used as threshold during processing. All the input parameters are listed in Table 3-4. Different colors illustrate that the parameters involved in different procedure steps.

Name	Description	Purpose	
ST	Size of each tile	Splitting the whole datasets into tiles	
OA	Area of overlap between two adjacent tiles	with suitable size	
$\Delta V t$	Maximum tolerance angle between generated		
Δ V ^ℓ thr	plane and vertical plane	Removing noisy object point	
Pm	Minimum proportion of point with multiple pulse	Removing holsy object point	
1 m ^{thr}	to whole number of point in the segment		
R.	Maximum radius for finding neighbors from each	Calculating the neighbors	
- thr	selected point		
Np_{thr}	Minimum number of point in a segment	Classification as terrain segment	
Npar _{thr}	Minimum number of points in boundary zone		
ΔHd	Minimum height distance between two adjacent	Measuring discontinuities	
<i>Linu</i> thr	segments	Weasuring discontinuities	
St _{thr}	Maximum slope in terrain segment		
Ps	Minimum proportion of segment points inside of a	Detecting the confidence level of	
1 S thr	tile to the whole number segment points	classification result in this tile	
Pls.	Minimum proportion of largest new segment size	Detecting corresponding segment	
1 ts _{thr}	to whole segment size	from different tiles	

Table 3-4: Parameters and their description



Figure 3-24: Parameters involved in the workflow

This chapter presented the methodology of filtering huge ALS data. All the parameters involved in the step of workflow are illustrated in Figure 3-24. The Implementation of the developed algorithm on large area of test site and results are presented in next chapter.

4. Implementation and results

4.1. Introduction

A strategy of filtering huge ALS data has been represented in chapter 3. Programming environment C++ and Mapping library are involved for designing this algorithm. An overall description of ALS system and research area is introduced in section 4.2. The ALS data examination is presented in section 4.3. The results of each step are expressed in section 4.4.

4.2. Given data and test site

4.2.1. Given data

The given datasets was provided by FLI-MAP 400 system (Figure 4-1) of company Fugro-Inpark. Due to relative low speed helicopter as aircraft, the point density in single strip is 20 points/square meter. This system consists of airborne laser scanner, two digital cameras and two video cameras. The relative accuracy of the laser points are 1-2cm. The system accuracy including GPS and IMU error source are 3-5 cm.



Figure 4-1:FLI-MAP 400 system (Fugro, 2007)

4.2.2. Test site

The site is located in the city of Enschede, the Netherlands. The site, with its extent of 750 m \times 750 m, is in the northwest of the city. Railway including railway bridge also is appeared in this site. In downtown area, closely located house along the street can be observed in this area. High-rise office building along the main avenue can be seen in this site. The roofs of this site have multiple shapes.

The site consists of residential house with adjacent dense vegetation. In the park, dense vegetation with low height also can be seen. The terrain is relatively flat.



Figure 4-2: Orthoimage of test site (source: Fugro)

4.3. Data examination

In reality, point clouds acquired by ALS system are not error free. In order to obtain accurate terrain segment, the distribution pattern of points in flat plane should be investigated for setting segmentation parameters.

The height range of points distributed in planar surface is from 1 to 4 cm in Figure 4-3. In order to cluster all the points from this planer surface, the tolerance height from candidate point to seed surface should a little bit higher than the height range.



Figure 4-3: Height range from planer surface

The Euclidian distance between two nearest points should also be investigated for accurate segmentation. This distribution pattern of laser points can be used for setting surface growing radius. The following Figure 4-4 shows the horizontal view of distribution pattern. The pattern of distribution also reflects the strip direction.



Figure 4-4: Distribution pattern in horizontal view

In reality, the terrain of this test site is a smooth surface. The height difference between highest and lowest terrain is about 7.3 meters. By investigating distribution pattern of points in flat plane, maximum distance to surface and surface growing radius as the two most important segmentation parameters can be optimized setting. The result of segmentation insures the terrain segment as an accurate continuous surface.

4.4. Implementation

When developed algorithm is applied on the test datasets, different input parameters are selected to achieve optimal result. Description of all the parameters is found in Table 3-4. In this research, the parameters are derived by two ways: various trials and visual examination. Table 4-1 lists all the optimal values for the parameters. The sensitivity of parameters is represented in chapter 5.

Name	Derivation ways	Value
ST	Trials	75 \times 75 meter
OA	Trials	15 meter
$\Delta V t_{thr}$	Visual examination	13 degree
Pm_{thr}	Trials	10%
R _{thr}	Visual examination	0.4 meter
Np _{thr}	Visual examination	13000 points
Npar _{thr}	Trials	60 points
ΔHd_{thr}	Trials	0.2 meter
St _{thr}	Trials	13.6 degree
Ps _{thr}	Trials	a)50% b) 25 %
Pls _{thr}	Trials	90%

Table 4-1: Value for parameters

4.4.1. Visual examination

Smooth segmentation parameters are selected by visual examination. If points in a segment belong to different class by visual examination, the parameters should be selected stricter to obtain accurate result. And if the surface of an object is not encompassed in one segment, tolerance parameters will be selected for smooth segmentation.

 R_{thr} is the parameter to determine neighbor points. If the range of detecting neighbor points from selected point is too large, the calculating time is increase. And in some cases, increasing R_{thr} lead to accept non-adjacent segment point. Thus, the topological description is inaccurate. Based on visual testing of the points distribution in 2D (Figure 4-4) and gaps between two adjacent segments, R_{thr} can be obtained. In different pass of filtering, object segments are removed. Then the topology of recognizing the adjacent segment is the two segments with near distance. Thus, gap between two adjacent segment two adjacent segment segment is complete the two adjacent segments increases and R_{thr} should increase also.

The threshold for maximum tolerance angle between generated plane and vertical plane ($\Delta V t_{thr}$) is generated by visual experience.

 Np_{thr} is obtained by visual investigating the generated segments and finding the biggest object segment.

4.4.2. Various trials

ST is the size of each tile. The tile size is depended on the point density and computer memory. And also each tile should have same size.

OA is to avoid detecting too many combination segments. The more OA assigned, the less combination segments should be detected but it will increase the tile size. To trade off, 15 meters is selected as the value. The reason is most object segment is not extent 15 meters.

Conceptually, all the points from two corresponding segments can be clustered as one segment. However, due to seed points for generating seed surface are arbitrary selected, there are more than one segment are generated by smooth segmentation. However, the largest new generated segment clusters most of the points and some small segments just clustering limited points. By trials, the largest new generated segment with its proportion more than 90% of whole point size.

4.4.3. Summary of parameter selection

In each pass of filtering, R_{thr} increases its value. $\Delta H d_{thr}$ can be assumed which has linear relation with R_{thr} . Then, $\Delta H d_{thr}$ should also increase in each pass. Other parameters are all fixed for any pass of filtering.

4.5. Result

By performing the developed filtering with optimal parameters, the results of each step are presented from Figure 4-5 to Figure 4-9. In each figure, the data before processing and the result after processing are showed.

Figure 4-5 illustrates removal wall and vegetation points. Points from raw data (Figure 4-5 (a)) are distributed on wall surface and crown of vegetation. After preprocessing, all the wall points are all removed. The terrain points near to wall are reserved. The fences in the top left corner of Figure 4-5 are also removed. Most of vegetation points are removed also. Though some of vegetation segments are reserved due to most points in these segments are not multiple return, all the object segments have distinctly height jump toward terrain segment. All planner surfaces of a roof are encompassed in one segment. Thus the topological description turns out to be simple and geometric area can be straight used for classifying terrain segment.



Figure 4-5: Result of preprocessing (before and after processing)

Figure 4-6 illustrates classification result in one tile. After preprocessing, segments become the element for classification. By visual investigation, there are some courtyard segments enveloped by roof segments. Figure 4-6 (b) shows the detected object segments. All roof, car and vegetation points are classified as object. Due to the geometric area is below the defined threshold, the courtyard and terrain segments are unclassified (Figure 4-6). The objects on the edge this tile is also not classified. By investigating the label of terrain and courtyard, the courtyards have the same label as terrain. The reason is the courtyard segments by measuring nearest terrain segment are merged into terrain segment. The terrain is a combination segment which can be classified by using information from multiple tiles.



(Before processing (a), classified segments (b), unclassified segments (c))

Figure 4-7 illustrates classification result of combination segment. The selected segment is on the right edge of the left tile. The corresponding part is on the left edge of the right tile. According to segment at the boundary of tile has low confidential level of classification, the segment should find its corresponding parts in different tiles. In this case, the segment is shared by two tiles. In the left tile, the selected segment is classified as object due to it has higher altitude than its local context. The segment in right tile also has discontinuous height in local context. Then, this combination segment can be assumed which has discontinuous higher than its full context. And also the number of points in this combination segment is below threshold. Thus this combination segment is classified as object segment.



Figure 4-7: Identify object from combination segment

In densely built-up area, dense buildings result in limited Bare Earth in single tile. This geometric area of this terrain segment is below the defined threshold (Figure 4-8). Then this segment will be unclassified. It is also take place when there is a deep depression in the terrain, the terrain segment

will be misclassified as object segment even. According to terrain as a continuous surface, this selected segment can find its corresponding part in adjacent tiles. After finding all corresponds, the geometric measurement of this combination segment with highest priority is first been used for classification. Otherwise, if one of the corresponding segments is classified as terrain with high confidence level, this whole combination segment will be classified as terrain.



Figure 4-8: Identify terrain from combination segment

The final DTM after merging all tiles is showed in following Figure 4-9. Traffic network can be recognized from DTM. The gaps along the road are the roof points which are removed by this algorithm. The small gaps in open area (box C) are the result of removing vegetation. The courtyards (box A and B) which are enveloped by object segments are accurate detected.

The railway bridge (box D) is classified as terrain by applying this filtering algorithm. The reason is the end side of railway bridge has a continuous surface connected to terrain. The surface growing in segmentation step will last from terrain to the whole bridge.

From the final result, the terrain is connected continuous surface. The terrain surface is connected by road and open area in the city. Except courtyards, all the terrain segments in each tile are connected to adjacent tiles.



Figure 4-9: DTM result

4.6. Summary

In this chapter, the developed filtering algorithm is tested by a large datasets. This testing datasets can not be segmented or classified in one go in computer memory. The test site with open area and with densely built-up is selected to test the algorithm. The wall and vegetation points are removed from preprocessing step. The accuracy segment is achieved by investigating distribution of points. Then the threshold value is derived by trial and visual examination.

From the visual checking, Courtyards are correctly detected as bare earth. The combination segments are classified accuracy. In next chapter, quantitative evaluation of result is described.

5. Validation and analysis

5.1. Introduction

In chapter 3, the filtering algorithm has been described. The result achieved from a test data with large area in chapter 4. The performance of this filtering algorithm is examined and discussed in this chapter. The strategy for performance evaluation is explained in section 5.2. The parameters for detecting and removing wall and vegetation points are analyzed in section 5.3. The sensitivity of algorithm parameters is represented in section 5.4. The extracted DTM quality is analyzed in section 5.5. The impact of tile size is described in section 5.6. The analysis of time consuming is introduced in section 5.7.

5.2. Strategy for performance evaluation

The developed filtering algorithm contains three steps. The input of next step is the output of previous step. In each step, some parameters and threshold values are involved. In order to optimal parameters setting, the result of each step should be evaluated. The reference data is the manually classified terrain reference. However, reference data is not suitable for evaluating result of each step but the errors can propagate to final DTM. Thus, visual examination, type I, type II error or unused points (named as Type III error) analysis are involved for evaluating result of each step.

5.2.1. Visual examination

In this research, segmented points are either classified as terrain or object. And the reference data do not provide sub-classified object points. That is impossible to quantity analyze the accuracy of wall and vegetation points extraction. However, the purpose of removing wall and vegetation points is to provide that object segments have distinguished height jump toward terrain. The visual examination is involved to detect whether there still remaining some wall and vegetation points (like vegetation or wall points).

5.2.2. Type I, Type II and Type III error

In some cases, terrain points are classified as object points and also object points can be classified as terrain points (Sithole and Vosselman, 2003). Type I error (reject terrain points) and Type II error (accept object points) can occur during either segmentation or classification step.

There is another error source that the points are not involved in classification step. In this research, these points which are not used for classification are named as Type III error and these points are considered as object points. Type III error is influenced by segmentation parameters. Some small clusters of points are unable to fit planes or number of points in this cluster is not reach the

minimum segmentation threshold. And also, classification of segments with low confidence level can be defined as unclassified segment.

In this research, an ideal site is selected from the whole datasets to find the optimal filtering parameters. This ideal site do not have object segment at its edges. The optimal segmentation parameters are selected by various trials. Thus, Type I and Type II and Type III error are discussed in effects of segmentation where Type III error is the points are not segmented. Quality assessment of final DTM result involved Type I, Type II and Type III error where Type III error here is the segment are not classified.

The cross-matrix table can be summarized after classification. The Table 5-1 is modified from ISPRS filter test.

		Filtering result			
		Bare earth	Object	Unused	Total
	Bare earth	а	b	С	a+b+c
Reference	Object	d	е	f	d+e+f
	Total	a+d	b+e	c+f	Т

Where:

a: Number of points which have been correctly classified as terrain

b: Number of terrain points which have been incorrectly classified as object

- c: Number of terrain points which have not been used
- d: Number of object points which have been incorrectly classified as terrain
- e: Number of points which have been correctly classified as object
- f: Number of terrain points which have not been used
- a+b+c: Total number of terrain points in reference data
- d+e+f: Total number of object points in reference data
- a+d: Total number of terrain points after filtering
- b+e: Total number of object points after filtering
- c+f: Total number of unused points after filtering
- T: Total number of points in reference data

By using the cross-matrix table, three Types of error and the total error can be calculated as percentage for comparison.

Error type	Result	
Туре І	(b+c/ a+b+c)×100%	
Type II	(d/ d+e+f) ×100%	
Type III	(c+f)/T×100%	
Total	(b+c+d)/T×100%	

Table 5-2: Table of error type (Nirodha Perera, 2007)

5.3. Parameters for removing wall and vegetation points

5.3.1. Parameters setting for detecting wall

Detecting wall can be achieved by checking whether planar segment is vertical. As wall segment can not be perfect vertical plane, the parameter defined the tolerance angle between candidate plane and vertical plane.

Two test sites are used for detecting wall points. In one site, only limited points distribute on the wall surface. In the other site, points with high density are on the wall. Visual examination and Type I error analysis are involved for evaluation.

5.3.1.1. Sample 1: low density of points on the wall

A list of variable setting for detecting wall is given in following Table 5-3.

ie 5-5. Valiable setting for	Totel alice aligie – lo	w density points on
Tolerance angle	Type Lerrer $(%)$	Visual exam
(degree)	Type Lettor (%)	result
1	0.11	Poor
5	0.16	Poor
9	0.30	Good
13	0.43	Good
17	0.46	Good
21	0.49	Good

Table 5-3: Variable setting for Tolerance angle – low density points on wall

From visual representation, some wall points are not segmented. Type I error occurs at the root of wall. The tolerance angle above 9 degree has a good visual result. As the tolerance increased, Type I error appears stable.



Figure 5-1: Type I error in extracting low density of wall points

5.3.1.2. Sample 2: high density of points on the wall

A list of variable setting for detecting wall is given in following Table 5-4.

Tolerance angle (degree)	Type I error (%)	Visual exam result
1	0.13	Poor
5	0.30	Poor
9	0.41	Poor
13	0.50	Good
17	0.53	Good
21	0.53	Good

Table 5-4: Variable setting for Tolerance angle – high density points on wall

Most of wall points are detected by applying this algorithm. As the tolerance angle increased, the total detected points are also increased. That is because with more tolerance angle with vertical, some vegetation segments are also involved. The Type I error also occurs at the root of wall.



Figure 5-2: Type I error in extracting high density of wall points

Two sites with different distribute pattern have similar parameter for detecting wall points. Tolerance angle with 13 degree has good visual examination result and relatively few Type I error points.

5.3.2. Parameters setting for detecting vegetation

To determinate the optimal parameters for detecting vegetation, Type I error and Type II error points are the two indices. Three samples of vegetation areas are involved. Sample areas have different height and density vegetation and the sample sites only contain vegetation and terrain.

Instead of comparing sensitivity of detecting parameters, two type of component pulse are compared here. According to the characteristics of vegetation segment, the percentage of "multiple pulse" or "not last pulse" toward whole number of points in a segment are used to detect vegetation. The percentage number is calculated by optimal result.

The result below illustrate the amount of vegetation points being detected and the percentage of Type I error and Type II error in three samples. The original site is on the left side. The first row is the result of using "not last pulse" type and the second row is using "multiple pulse" type.

5.3.2.1. Sample 1: dense forest

This sample is covered by dense high forest. Using the type of "not last pulse", low vegetation segments can not be detected as vegetation. The remaining vegetation points are closed to the terrain. By using the type of "multiple pulse", Type II error reduced whereas Type I error increase.

Original site	Result of removing vegetation	Type I error	Type II error
		1	

Figure 5-3: Sample 1: high dense forest

5.3.2.2. Sample 2: vegetation in open area

This sample is covered by few high trees. Using the type of "not last pulse", Bare Earth enveloped by vegetation is reserved but low vegetation segments are still remained. The remaining vegetation segments which near to the Bare Earth increase Type II error. By using the type of "multiple pulse", Type II error decrease since the low vegetation segments are removed. However, some bare earth segments are also removed. Thus increase Type I error.

Original site	Result of removing vegetation	Type I error	Type II error	

Figure 5-4: Sample 2: vegetation in open area

5.3.2.3. Sample 3: low vegetation

This sample is covered by low vegetation. Comparing with not last pulse type, multiple pulse type also has less Type II error but more Type I error.

			1 4 8 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Original site	Result of removing vegetation	Type I error	Type II error
1	1		

Figure 5-5: Sample 3: low vegetation

According to the results of the three different type of site, though Type I error using "not last pulse" method is less than using "multiple pulse" method, the type II error using not last method is much more than using multiple method. The aim of this research is to extract accuracy DTM. The object points should be removed as many as possible. The sensitive of Type II is much more than Type I error and reduce Type II error is most important. Thus it is make more sense to use "multiple pulse" type.

5.4. Sensitivity of filtering parameters

5.4.1. Maximum distance to surface

The quality of segmentation depends on segmentation parameters. In this research, KNN as the model is to define neighborhood in segmentation step. Since most points are clustered by surface growing, "maximum distance to surface" is the most effective parameter. In section 5.4, an ideal site with no object segment on the edge. This site is large enough to detect terrain segment by measuring number of points. All the classification results are with high confidence level.

When a seed plane is generated, all the neighbor points are become the candidate points. The candidate point will be clustered to this segment when the distance to seed surface is smaller than defined segmentation parameter. This parameter named Maximum distance to surface.

In order to include as many as same attribute points into a segment and exclude points with different attribute, Maximum distance value should be defined by trials. By fixing other parameters, the three type of error using various value of maximum distance is showed in Figure 5-6.



Figure 5-6: Sensitivity of maximum distance to surface

The above figure illustrates the gradual increase of maximum distance to surface. Due to wall and vegetation points are removed in preprocessing step, Type I error do not have influence from increasing distance. At the same time, Type III error decreases because more unclassified points are clustered to segment. Type II error increases because unclassified object points close to the terrain are clustered. To trade-off Type II and Type III, the distance with minimum overall error (0.35) is used as optimized parameter.

5.4.2. Parameter optimization in classifying single tile

Performance of evaluation filtering result is performed using the ideal datasets.

As searching neighbor radius (R_{thr}) increase in each iteration of filtering, the height difference between two segments (ΔHd_{thr}) should be increased also. In this research, it is assumed that these two parameters have linear relationship. Since take street curb into account, when R_{thr} is zero, ΔHd_{thr} should be 0.3 meter. Thus the intercept of linear relationship is zero. The slope of linear relationship depends on the maximum inclination in terrain. For example, the maximum slope in terrain is 10 degree, thus 0.175 as the ratio is used.

The following table lists these two values in each pass.

Iterative	1	2	3	4	5	6	7	
R _{thr}	0.4	0.8	1.6	3.2	6.4	12.8	25.6	
ΔHd_{thr}	0.37	0.44	0.58	0.86	1.42	2.54	4.78	

Table 5-5: Variable set for filtering parameter optimization

The affect of the maximum terrain slope value is tested by the result of optimal segmentation. Due to all segments in this site are classified, there are not Type III error. The Type I, Type II and overall error is illustrated in following figure.



Figure 5-7: Sensitivity of ratio

As the value of ratio increasing, The Type I error decreases rapidly when the ratio changes from 0.1 to 0.12 and then appears stable. Type II error do no impact from the various setting of slope. Hence, from Figure 5-7, 0.18 with its lowest overall error is selected as optimum value for ratio.

5.5. Analysis of Optimum Result

By applying the optimum parameter, the whole datasets is tested by this filtering and combination algorithm. The result below is illustrated by following table:

Error type	Final result		
Туре І	1.38%		
Type II	5.07%		
Type III	4.41%		
Total	7.10%		

Table 5-6: Summary of classification result

For visual representation of errors from Figure 5-8, Type I error within this large site is relatively small. The small clusters of points are the error from segmentation step. Only the courtyards near the edges of the block are misclassified. There is no combination segment which is misclassified in Type I error.

Type II error is relatively high. A large segment on the left side of Type II error is because of railway bridge is detected as terrain in this developed algorithm. Other small clusters of points are the low vegetation points which are clustered as terrain segment. It is obviously that the upper part of test site has more Type II error than the lower right corner. The reason is more low vegetations generate more Type II error. The small clusters of points are also the error from segmentation step. There is no combination segment misclassified in Type II error also.

Type III error are the segments which are unclassified. The unclassified segments only locate intersect the edge of the block. All the combination segments are classified.



5.6. Influence of dividing

As the development of ALS system, more dense points per square meter will be obtained. In order to apply filtering algorithm for this case, the whole datasets should be decomposed to smaller tile. In this section, the developed algorithm is performed on various size of tile to evaluate the performance. The given datasets is split into various sizes in different time and with different overlap area.

5.6.1. Impact of overlap

In this research, the whole datasets is firstly divided into original tiles and then assign buffer area for each tile. Thus the value of buffer area also impacts the tile size. On the other hand, overlap area can be used for avoid too many segments being detected as combination segments. The optimum width value of buffer area can be achieved by investigating the number of combination parts remain in all tiles and the size of each tile. Figure 5-9 illustrates the relation with buffer width and number of combination parts. The original tile size without buffer area is fixed as 75×75 meter.



Figure 5-9: Effect of buffer width

From above figure, the remarkably decrease of the number of combination parts when buffer width changes from 10 m to 15 m. The reason behind is most object segment are not extent to 15 meter. As the buffer width increase, number of combination part decrease slowly. Using property buffer width can avoid too many segments as combination segments and keep suitable size of tile.

5.6.2. Impact of tile size

The tile size also impacts the performance of this algorithm. As higher point density will be obtained in further, the results of performance in various tile size is illustrated in below figure:



Figure 5-10: Impact of tile size

The figure illustrate as the tile size decrease, Type III error increase but other two Type of error remain the same. The Type III error here is not the points are not segmented but the segments are not classified. The reason for increasing unclassified segments is that the lowest segments in some tiles can not be classified and these segments are not combination segment. For example, a courtyard segment is enveloped by roof segment in one tile (Figure 5-11). The object segment belongs to combination segment and can be classified using information from multiple tiles. However, the courtyard segment is the lowest segment and do not belong to combination segment. This courtyard segment is relatively small and can not be classified by geometric area. Thus this courtyard segment is the result of unclassified segment.



Figure 5-11: Unclassified courtyard in small tile size

5.7. Analysis of time consuming

The developed algorithm has three steps of procedure. In preprocessing step, creating a block and dividing into tiles are deal with the whole datasets. The removing wall and vegetation points in preprocessing step and filtering step are performed in individual tile. Then, the stages of finding corresponding and deriving DTM are processed with all tiles in the same time.

The time of creating tile mainly depends on the size of the whole datasets. In this research, the size of single tile is 105×105 meter including buffer. The processing time from raw data to classified result is around forty-eight minutes for each tile. Most of the time is occupied for detecting wall and vegetation points.

Classifying incomplete segments is the most time consuming step. By detecting and classifying among 100 tiles, it costs two hours. An alternative way of detecting corresponding segments is using connected component. Connected component method reduces twenty-five minutes in this step comparing to smooth segmentation. These two approaches of detecting corresponding parts give the same result. However, the validation of connected component should be further investigated.

The final step of merging all tiles takes relatively short time (around half an hour).

5.8. Summary

In this chapter, different performance evaluation results have been discussed based on the optimum parameters. After preprocessing, the Type I error is low in final result. The overall error can be reduced by using proper parameters. By visual examination of combination segments, smooth segmentation algorithm can be used for detecting corresponding parts from adjacent tiles. The results of classification based on segment have high accurate, whereas most of error source is from segmentation step. This developed algorithm is suitable for the datasets with the tile size more than 45×45 m. As tile size decrease, more segments can not be classified and the Type 3 error increase.
6. Conclusion and further work

6.1. Conclusions

The main aim of this research is to design a splitting and combination algorithm for huge datasets to extract DTM. To achieve this objective, five questions have been answered.

The first question is: how to achieve accurate segment? The property of wall and vegetation points and different performance of planar and smooth segmentation have been analyzed and three conditions are built to remove wall and vegetation points

The second one is: How does the classification algorithm work? Based on the generated segments, topological and geometric descriptions can be achieved. Using those descriptions, all the generated segments can be categorized as six cases in Table 3-2. Among the six cases, three of them can be classified. Other cases transfer themselves to the three cases by changing topological and geometric descriptions.

The third question is: Which algorithm can be used for detecting incomplete segments in different tiles? Surface growing in smooth segmentation is used for detecting surface parameters and roughness. The candidate segments which are put in object space are grew as one segment when they are the parts of one combination segment.

The fourth one is: How to classify combination segments? The classification result in each corresponding tile is used. By analyzing various situations of combination segments, another classification algorithm is applied on those segments.

By applying the algorithm on various tile sizes, the relation between tile size and quality of extracted DTM is analyzed. Based on the obtained result and performance evaluation, following conclusions are drawn:

- Successful detection of combination segments from multiple tile illustrates that Surface growing in smooth segmentation can be used in detecting them. However, the smooth segmentation parameters have strong impact of detecting threshold value. Due to seed points are arbitrary selected, the result of smooth segmentation is Unpredictable.
- The classification result of combination segments can help to improve the quality of extracted DTM. This classification algorithm considers local context of every corresponding part and take the whole geometric information into account.
- The generated algorithm can be applied on the tiles with the size larger than 45×45 m.
 Generally, quality of derived DTM has direct relationship with the tile size when it is small.

6.2. Recommendations

Some recommendations are listed as follow to robust this developed algorithm:

Improvement segmentation result

This algorithm only uses the spatial pattern for segmentation. The only source to apply segmentation leads to low accurate result. For example, in order to include road curb as part of DTM(Liang, 2009), some points distributed on the surface of low bush are also clustered in terrain segment. External sources like aerial photos can be used to improve the accuracy of segment. The full waveform of laser beam is also a potential source for improving segmentation result.

Reduce points for classification

Since only points inside the boundary zone is used for classification, a strategy for finding boundary zone points can be developed in the further. After dividing datasets and detecting combination segments, only points at the boundary zone are remained for classification. This strategy can be used to reduce the number of points in each decomposed tile. Thus, several tiles can be combined for classification. Reduce unnecessary points may be the solution for classifying the extreme small size of tile.

Parameter optimization

In this research, smooth segmentation is used to generate segment. The advantage for that is smooth segment can be easily used for detection corresponding parts from other tile. The disadvantage is that more Type II error increases by using smooth model (Nirodha Perera, 2007). From the result, error source mostly come from segmentation step. Thus, the optimal parameters and the model of surface growing model should be carefully investigated even though it is a time consuming work.

Detecting long extent bridge

The railway bridge is recognized as terrain in this research. (Sithole, 2004) proposed a method to detect bridges from ALS data. However, his research is achieved by the bridge is complete in one file. It should be investigated the bridge extent several tiles.

7. Bibiliography

- AXELSSON, P. 1999. Processing of laser scanner data--algorithms and applications. In: ISPRS Journal of Photogrammetry and Remote Sensing: 54, 2-3, pp. 138-147.
- AXELSSON, P. 2000. DEM generation from laser scanner data using adaptive tin models. *In: IAPRS* 2000 : Vol. XXXIII, B4/1, Amsterdam, The Netherlands, pp. 110-117.
- COLUMBIA, U. O. B. 2009. Available: <u>http://www.forestry.ubc.ca/Portals/100/Topic%2012-</u> <u>%20Photogrammetry%202009.pdf</u> [Accessed January 4, 2010].
- DONEUS, M., BRIESE, C., FERA, M. & JANNER, M. 2008. Archaeological prospection of forested areas using full-waveform airborne laser scanning. *In: Journal of Archaeological Science: 35*, 4, pp. 882-893.

FILIN, S. & PFEIFER, N. 2006. Segmentation of airborne laser scanning data using a slope adaptive neighborhood. *In:ISPRS Journal of Photogrammetry and Remote Sensing:* 60, 2, pp.71-80.

- FUGRO. 2007. *FLI-MAP 400* [Online]. Available: <u>http://www.flimap.com/site4.php</u> [Accessed January 7 2009].
- KILIAN, J., HAALA, N. & ENGLICH, M. 1996. Capture and evaluation of airborne laser scanner data. *In: IAPRS 1996: Vol. XXXI, B3, Vienna, Austra, pp. 383-388.*
- KRAUS, K. & PFEIFER, N. 1998. Determination of terrain models in wooded areas with airborne laser scanner data. In: ISPRS Journal of Photogrammetry and Remote Sensing: 53, 4, pp. 193-203, 53, 193-203.
- LEE, I. & SCHENK, T. 2001. 3D perceptual organization of laser altimetry data. *In: IAPRS 2001, 34, Part 3/W4, pp. 57-64.*
- LEE, I. & SCHENK, T. 2002. Perceptual organization of 3D surface points. In: ISPRS Commission III, Symposium. Graz, Austria.
- LIANG, Z. 2009. Extraction of road sides from high point density airborne laser scanning data. ITC.
- MALLET, C. & BRETAR, F. 2009. Full-waveform topographic lidar: State-of-the-art. In: ISPRS Journal of Photogrammetry and Remote Sensing: 64, 1, pp. 1-16.
- NARDINOCCHI, C., FORLANI, G. & ZINGARETTI, P. 2003. Classification and filtering of laser data. *In: IAPRS : Vol. XXXIV, Dresden ,3/W13 , Germany.*
- NIRODHA PERERA, G. S. 2007. Segment based filtering of LASER scanner data. ITC.
- PFEIFER, N., STADLER, P. & BRIESE, C. 2001. Derivation of Digital Terrain Models in the Scop++ Environment. In: OEEPE workshop on Airborne Laser Scanning and Interferometric SAR for Detailed Digital Elevation Models, Stockholm, Sweden.
- RABBANI SHAH, T. 2006. Automatic reconstruction of industrial installations : using point clouds and images. Nederlandse Commissie voor Geodesie (NCG).

- SITHOLE, G. 2001. Filtering of laser altimetry data using a slope adaptive filter. *In: IAPRS 2001: Vol. XXXIV 3/W4*, *Annapolis (MD), USA, pp. 203-210.*
- SITHOLE, G. 2004. *Segmentation and classification of airborne laser scanning data*. Nederlandse Commissie voor Geodesie (NCG).
- SITHOLE, G. & VOSSELMAN, G. 2003. Comparison of filter algorithms. *In: IAPRS 2003: Vol. XXXIV 3/W13*.
- SITHOLE, G. & VOSSELMAN, G. 2004. Experimental comparison of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds. *In: ISPRS Journal of Photogrammetry and Remote Sensing: 59, 1-2, pp. 85-101.*
- TÓVÁRI, D. & PFEIFER, N. 2005. Segmentation based robust interpolation—a new approach to laser data filtering. *In: IAPRS 2005 : Vol. XXXVI, 3/W19, Enschede, The Netherlands, pp. 79-84.*
- VOSSELMAN, G. 2000. Slope based filtering of laser altimetry data. In: IAPRS 2000 : Vol. XXXIII, 3/W19, Amsterdam, The Netherlands, pp. 935-942.
- VOSSELMAN, G., GORTE, B. G. H., SITHOLE, G. & RABBANI, T. 2004. Recognising structure in laser scanner point clouds. In: IAPRS 2004 : Vol. XXXVI, 8/W2, Freiburg, Germany, pp. 33-38.
- VOSSELMAN, M. G. 2009. Advanced point cloud processing. In: Photogrammetric Week '09 / ed. by. D. Fritsch. Heidelberg : Wichmann, 2009. ISBN 978-3-87907-483-9. pp. 137-146.
- WANG, X. & ZHAO, S. 1994. Automatic combination of lines in vectorized maps. In: Journal of Xidian University: 21, 4, pp. 37-43.
- ZHANG, K., CHEN, S., WHITMAN., SHYU, M., YAN, J. & ZHANG, C. 2003. A progressive morphological filter for removing nonground measurements from airborne LIDAR data. *In: IEEE Transactions on Geoscience and Romote Sensing: 41,4, pp. 872-882.*

Appendix – A

Optimal segmentation parameters for developing the algorithm are shown in following:

Segmentation parameters	Segmentation method		
	Planer segmentation	Smooth segmentation	Surface growing for detecting
Neighborhood definitions			
Storage model	Kd-tree		
Number of neighbors in Kd-tree	20	30	30
Seed selection parameters			
Maximum slope angle	90	90	90
Bin size slope angle	0.2	0.3	0.35
Minimum number of seed points	10	10	10
Maximum distance to plane	0.2	0.15	0.2
Surface growing Parameters			
Surface model	Planer	Smooth	Smooth
Surface growing radius	0.25	0.3	0.4
Maximum distance to surface	0.15	0.2	0.35
Minimum number of points	10	100	500