Segmentation Based Classification of Airborne Laser Scanner Data

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Abstract

This work provides an approach for classification of airborne laser scanner data. Airborne laser scanning (ALS) has become a widely used data acquisition technique in the field of topographical mapping. ALS acquires point coordinates around the earth's surface and in addition the objects on it. So called digital surface models (DSM) can be generated from the measurements. DSM contains the terrain, vegetation, buildings and other objects that can be seen on the earth's surface. Terrain points can be extracted from this model in order to build digital terrain models (DTM). This procedure is called filtering. Many applications are based on these two models.
Besides the selection of the terrain surface, there is an emerging demand for extraction of additional information from the measurements like the determination of buildings or vegetation. Measurements can be classified according to the type of the objects that are measured. Classification of points is a precondition of many applications, e.g. class dependent object modelling or class dependent filtering.
Of course, data fusion - i.e. the integration and use of additional data - can simplify this procedure, but on the one hand, these data are often not available and on the other hand, the slow acquisition of other data can hinder the fast data processing. The point density and accuracy of ALS data enables us to recognise the terrain and building points as well as higher vegetation with a high reliability. Other objects like vehicles or lower vegetation can not be classified reliably, due to the fairly few samples.
The current filtering methods consider features like the relative position of neighbouring points and segments respectively, or the distance between the point and the approximated surface. These features can not provide sufficent information for an adequate filtering. This lack of reliable information may lead to filtering errors that can be corrected only by manual work.
The classification of ALS data consists of the separation of terrain and object points, and the recognition of buildings and vegetation. The first step - by means of a so-called filtering method - a classification of points into terrain and object points is performed. In the literature two approaches - i.e. general strategies for solving the problem - can be identified for filtering. The first one works directly on the measured points and geometric criteria are used to make the decision if a point is on the ground or an object point. The methods of the second approach is to segment the data as a first step and then perform a classification based on segments. The new approach for filtering combines both approaches, specifically exploiting their strengths. This method is based on a new feature, namely on the distance between the segments and the approximated terrain surface. This feature could be applied

later in a filter which combines all possible point and segment features and a classification is performed based on these features. Planes are segmented in the first step of the method. It means, points are joined together that belong to the same plane surface. A point is connected to the surface if it fulfills certain geometrical requirements. Than a decision is made, if a segment is a part of the terrain or it is a part of an object. Terrain segments provide the basis for the DTM generation.

Classification of buildings and vegetation is based on objects, because a pixel-wise classification - especially when using laserscannning data - is limited in terms of reliability of its results. Therefore, the first step of this approach will be a segmentation of 3D objects. For segmentation a normalised digital surface model (nDSM) is generated by subtracting a digital terrain model (DTM) from the original laser data (DSM). Now, 3D objects can be segmented by means of a specific region growing algorithm on this nDSM. The classification of the segmented objects may be performed by different methods. Both maximum likelihood methods; and fuzzy decision making systems are suitable for this purpose. The classification of samples is based on the features of the objects, therefore, different kinds of object-oriented features are determined for each segment, like height texture, border gradients, first/last pulse differences, shape parameters or laser intensities. The reliability of these features are investigated and presented. Data acquired by different scanners have different characteristics, therefore, the robustness of the approach is tested as well.

For a complete high vegetation classification, the vegetated areas are detected based on the first and last pulse differences. The results show that not only terrain but also buildings and vegetation can be classified reliably from ALS data. The reliability of the features and the robustness of the methods are analysed.

The presented classification is a general approach, since not only these particular filtering, segmentation and classification techniques can be used. This general behaviour is a great advantage of this strategy. The results show the capability to obtain a higher filter reliability with segmentation based filters. These filters are superior to point based filters especially, where the topography contains step edges and breaklines. The filter results depend on the quality of segmentation, since the segments should be homogeneous. The approximation of terrain with plane surfaces can not provide sufficient segments in every case, so the terrain segmentation has to be improved later.

The classification of objects on the basis of extracted features provides about 90% classification rates. Both fuzzy logic and maximum likelihood method produce similar suitable results. Different kinds of objects (e.g. vegetation and building) merged within a segment may confuse the classification, therefore, different kind of objects should be separated. High vegetation can be detected on the basis of first and last pulse differences, while low vegetation can not be classified reliably in airborne laser scanner data.

Kurzfassung

Diese Arbeit beschreibt einen Ansatz zur Klassifizierung von flugzeuggetragenen Laserscannerdaten (ALS-Daten). Im letzten Jahrzehnt ist ALS eine weit verbreitete Datenerfassungstechnik für topographische Anwendungen geworden. Die Laserscanner-Technologie sammelt Punktkoordinaten von der Erdoberfläche und den auf ihr befindlichen Objekten. So genannte Digitale Oberflächemodelle können aus diesen Daten gewonnen werden. Das Digitale Oberflächenmodell enthält nicht nur das Gelände, sondern auch die Vegetation, die Gebäude und alle andere Objekte, welche auf der Erdoberfläche zu finden sind. Aus diesem Modell kann man die Geländepunkte extrahieren und das Digitale Geländemodell (DGM) aufbauen. Dieser Arbeitsschritt heißt Filterung. Die Anwendungsmöglichkeiten, die auf diesen zwei Modellen basieren, sind vielfältig. Bei vielen Anwendungen besteht ein Bedarf an Klassifizierung der Punkte. Neben der Selektion der Erdoberfläche, es gibt steigenden Bedarf zur Extraktion zusätzlicher Daten wie Bestimmung von Gebäuden und Vegetation. Die Messungen können klassifiziert werden nach den gemessenen Objekten. Klassifikation der Messungen ist eine Bedingung für viele Anwendungen wie klassenabhängige Objekt-Modellierung oder klassenabhängige Filterung.

Obwohl Daten-Fusion - d.h. Integration zusätzlicher Daten - die Klassifizierung vereinfachen könnte, sind diese zusätzlichen Daten oft nicht verfügbar und die Erfassung dieser Daten würden eine schnelle Datenverarbeitung behindern. Die Klassifikation der Laserscanner-Daten schränkt sich im Fall der vorliegenden Arbeit auf die Extraktion der Geländepunkte und die Detektierung der Gebäude und der höheren Vegetation. Andere Objektarten wie niedrigere Vegetation können nicht klassifiziert werden, wegen der relativ geringen Punktdichte. Dazu werden die Objekt- und Geländepunkte im ersten Schritt separiert.

Die aktuellen Filtermethoden betrachten nur Merkmale wie die 'relative räumliche Position' der benachbarten Punkte bzw. Segmente oder die 'Entfernung der Punkte von der Approximation der Oberfläche'. Diese Merkmale oder Informationsquellen können nicht genügend Information zu einer ausreichend zuverlässigen Filtermethode liefern. Dies kann zu Fehlern der Filterung führen, die zur zeit oft nur durch manuelle Bearbeitung korrigiert werden können.

In der Literatur sind zwei wesentliche Strategien zur Filterung beschrieben. Die erste bearbeitet direkt die Punkte aufgrund spezieller geometrischer Kriterien, um zu entscheiden, ob ein Punkt zum Gelände gehört oder nicht. Das zweite Verfahren segmentiert zuerst die Daten und klassifiziert anschließend diese Segmente. Das neue Verfahren kombiniert beide Strategien, um ihre jeweiligen Vorteile zu nutzen.

Im ersten Schritt der Methode werden Ebenen segmentiert, d.h. die Punkte, die zu derselben Oberfläche gehören, werden zusammengefasst. Ein Punkt wird zu einem Segment hinzugefügt, wenn er bestimmte geometrische Voraussetzungen erfüllt. Danach wird entschieden, welche Segmente Teil der Geländeoberfläche, und welche Objekte sind. Die Gelände-Segmente liefern die Basis für das DGM.
Die Qualität der Filterung hängt von der Qualität der Segmentation ab. Die Segmente müssen sehr homogen sein, da diejenigen Segmente, die sowohl Objektpunkte als auch Geländepunkte enthalten, falsch klassifiziert werden können. Diese Filtermethode nutzt ein neues Merkmal -nämlich die Entfernung zwischen der Trendfläche und den Segmenten-, das auch später in einem neuen Filterungsansatz benutzt werden kann. Das klassifizierungsbasierte Verfahren würde alle extrahierbaren Merkmale und Informationsquelle zur Filterung verwenden.
Die pixelbasierte Klassifizierung der Laserscanning-Daten kann keine zuverlässigen Ergebnisse liefern, weil hier zu wenige Merkmale einbezogen werden können. Deshalb basiert die Klassifizierung auf Segmenten. Zur Definition der Segmente muss ein so genanntes normalisiertes Digitales Oberflächemodell (nDOM) hergestellt werden, das im Wesentlichen nur noch die Objekte der Oberfläche ohne Topographie enthält. Der Einfluss der Topographie wird dabei durch Subtraktion eines DGM eliminiert. Diese Objekte werden mit bestimmten Verfahren als Segmente extrahiert. Dazu wird ein Regionenwachstumsalgorithmus eingesetzt. Innerhalb der Segmentfläche werden die zur Klassifikation benötigten objektbezogenen Merkmale extrahiert, wie Randgradienten, Höhen-Textur, First- /Last-Pulse-Differenz, Form, Größe oder Intensität. Diese Segmente können dann aufgrund dieser Parameter mit Hilfe der Fuzzy-Logik oder eines statistischen Ansatzes klassifiziert werden. Verschiedene Methoden wurden in der Fuzzy-Logik untersucht, wobei die besten Ergebnisse mit denen der Maximum-Likelihood Methode verglichen wurden. Zu einer vollständigen Vegetationserkennung werden die Vegetationsbereiche aufgrund der First- /Last-Pulse-Differenzen der Pixel detektiert. Die Ergebnisse zeigen, dass nicht nur Gelände, sondern auch Gebäude und Vegetation ausschließlich aus Laserscanner-Daten klassifizierbar sind. Die Zuverlässigkeit der verschiedenen Merkmale und die Robustheit der Methode wurden analysiert.
Der Vorteil dieses Ansatzes ist, dass es eine generelle Methodik liefert, d.h. nicht nur diese speziellen Verfahren sind geeignet, sondern auch andere Filterungs- und Segmentierungsmethode können verwendet werden. Fuzzy-Logik bietet eine breite Auswahl an Lösungsmöglichkeiten der Klassifizierung und sie kann an die extrahierbaren Objekt-Merkmale angepasst werden.
Die Ergebnisse dieser Arbeit stellen die hohe Zuverlässigkeit der segmentbasierten Filterung dar. Diese Filtermethode liefert bessere Ergebnisse als die punktbasierte, besonders wenn die Topographie Kanten enthält. Die Segmente müssen homogen sein, weil das Ergebnis der Filterung von der Qualität der Segmentierung abhängt. Die Segmentierung des Geländes mit Hilfe von Ebenen kann nicht in jedem Fall die Besonderheiten des Geländes berücksichtigen, so dass noch ein Bedarf zur Verbesserung der Methode besteht.
Die Klassifikation der Objekte mit Hilfe der extrahierten Merkmale liefert ungefähr 90% Klassifikationsrate. Sowohl Fuzzy-Logik als auch die Maximum-Likelihood-Methode pro-

duzieren geeignete Ergebnisse in nahezu gleicher Qualität. Unterschiedliche Objekttypen, die fälschlicherweise in einem Segment zusammengefasst sind, führen u.U. zu Fehlern in der Klassifizierung. Deshalb müssen die Objekte der unterschiedlichen Klassen separiert werden. Hohe Vegetation ist zuverlässig detektierbar, während niedrige Vegetation aus Laserscannerdaten nicht klassifiziert werden kann.

Contents

Chapter 1

Introduction

1.1 Background

This thesis contains the research results of the project "Analysis of airborne laser scanner data for digital terrain model extraction in regard to hydrodynamic numeric models" ("Analyse von Laserscannerdaten zur Erzeugung Digitaler Geländemodelle für hydrodynamisch-numerische Berechnungsmodelle"). The project started in the interdisciplinary study and research group "Graduiertenkolleg Naturkatastrophen" at the University of Karlsruhe in December 2002. The project announcement determined a wide palette of task possibilities in the field of airborne laser scanning and hydrology. These tasks were:

- Improving the digital terrain model extraction
- Classification of vegetation and building objects
- Improving a method for selection of representative terrain points
- Investigation of water level extraction from airborne laser scanner data

Two of them have been chosen to be investigated, namely the digital terrain model extraction and the object classification. These tasks seemed to be very important in airborne laser scanning applications and these two can be applied widespread.

Laser scanning acquires 3D point measurements of the area of interest with high density within a very short time. A huge amount of data, which are densely measured samples allows the surface modelling of the gathered object. In contrast to photogrammetry or terrestrial surveying, laser scanning is not able to measure exact point positions or structure lines, since the sampling direction can not be controlled. Laser scanner measurements therefore provide excellent information about surfaces, but the acquisition of structure lines and pointwise objects is a random process, their extraction from the measured point cloud is a task of data processing. According to the sensor platform, the system can be a terrestrial laser scanner (TLS) or airborne laser scanner (ALS). Besides the similarity of these systems, the gathered data have different characteristics, therefore data processing differs as well. In this thesis, exclusively ALS applications are discussed.

1.2 Motivation

It is motivated by an emerging demand for automated data processing for high quality terrain models and for gathering additional information from airborne laser scanner data. The huge number of engineering applications (see in chapter 2.3) using digital terrain models shows that it is still worth developing filtering algorithms, which can select the ground points with a very high reliability, producing better results than today is existing methods. With the development of data processing methods, new applications are developed in order to exploit more and more information from the measurements. Object modelling like building reconstruction or vegetation modelling became an important application: building models are used e.g. to the system optimisation of telecommunication antennas, for selection of photovoltaic devices or even to tourist information systems and energy demand approximation in mega cities; vegetation modelling is used in forestry and in urban planning. These are only a few examples, but it shows that many applications are based on a class dependent modelling, which requires classification of the single measurements. Hydrological aspects provide motivation for object classification as well. The runoff is highly affected, among others, by the topography of the terrain, soil and the objects on the terrain surface. Different type of objects may have different resistance to the water flow. In a digital surface model from laser scanner data, vegetation and buildings may have the same ground area and volume, however, their resistance to the flow is completely different. From the huge amount of measurements, more information can be extracted rather than joining points to build a model. These can be e.g. breaklines (Briese, 2004) or properties and classes of surfaces. However, manual data processing is possible as well, but it takes extremely long processing time so it is not cost efficient. Therefore, the advantage of short data acquisition time vanishes. Acquired data in digital format gives a good chance for automated processing. Manual error correction in the automated processes is a very time consuming task, therefore, the quality enhancement of these processes is necessary.

1.3 Aims of the investigation

This thesis aims to offer new solutions for digital terrain model generation and ALS data classification. High quality results are required in respect of automation level and classification accuracy.

The main goal of the thesis is, therefore, to present an accurate and reliable approach for ALS data classification that detects terrain points first and then divides the object points either into a building or into a vegetation class. The process is based exclusively on ALS data in order to take advantage of the technique (see chapter 2.1).

1.4 Terms and expressions

In the literature about airborne laser scanning, some of the phenomena are described with various expressions and terms. The technique itself, airborne laser scanning (ALS), is also known as lidar (Light Detection And Ranging) and as airborne laser mapping (ALM). In this thesis, consequently, the first term will be used. In other cases, various words will be used for the description of one object or phenomenon. As an example, the terrain is mentioned as ground or bare earth as well.

1.5 Structure of this work

In the first part of the work (chapter 2), an overview of ALS and about digital terrain model generation from airborne laser scanning data is presented. In the next chapter (3) the frame of an own classification method is presented shortly. In chapter 4, existing filtering methods are systemized in a new way. This part determines the approach of the new segment based DTM extraction as well. Some segmentation and classification methods are presented in chapter 5 and 6, and the problems of the task are discussed. In these chapters, a new segmentation and classification method will be presented as well that focuses on the classification of terrain, vegetation and building segments. In the last part (chapter 7), experiments and evaluation of the methods will be demonstrated. Some partial results of my own investigations are presented in the chapters, where theories are presented, in order to give examples and make the theory clear. Sometimes these investigations are only mentioned. In these cases, results are important to be mentioned, but not important enough to be shown.

Chapter 2

Airborne Laser Scanning (ALS) overview

2.1 Introduction

In this chapter, ALS principles and some application possibilities will be presented briefly. This theme is elaborated on in other works: see the bibliography (Lohr, 1999 and Baltsavias, 1999).

Airborne Laser Scanning is a scanning and ranging method, which produces three-dimensional, highly accurate information and very high-resolution topographic models by direct measurement. The technology is also called Light Detection and Ranging (LIDAR).

The first laser measuring systems were built in the 1970s, these Airborne Profile Recorders (APR) acquired profiles of the Earth's surface by range measurement (Zarzycki, 1972, Ackermann, 1974). Precise planimetric position of the airplane could not be determined and, for this reason, the measurement suffered from a lack of precision. The renewed innovation could only be possible after the issue of commercial GPS and inertial navigation systems (INS), which make precise georeferencing possible. Commercial applications of the technology have been developed since the beginning of the 1990s. Nowadays, the whole procedure is semi-automated, from the flight planning up until the generation of digital surface or terrain models. ALS provides a time and cost efficient data acquisition method for topographic applications. Development of the technology is based on three main components: the hardware, the calibration and the data processing development. This thesis focuses exclusively on data processing, because this field in itself also offers a wide scale of topic possibilities for research.

Although, photogrammetry makes the cost efficient, relative fast landscape mapping with high accuracy possible, there is an emerging demand for more automated technologies. ALS offers a time efficient landscape measurement technique, with 0,1-0,2m vertical and 0,3-0,8m planimetric accuracy. The active system can provide a very dense point cloud ($>1\ point/m^2$). ALS and photogrammetry are regarded as related technologies, since both of them are highly accurate landscape measurement techniques and both instruments are mounted on aircraft. Due to these similarities, they can be compared from the user's point of view. ALS has some features which makes it more attractive in a lot of applications:

- While photogrammetry highly depends on the weather, ALS is less dependent on the weather and environmental conditions. Shadows do not have any effects on the measurements. Additionally, this technique is active, therefore, it can be used not only in daylight, but also at night, regardless of the season.
- While photogrammetry needs an experienced operator for mapping, ALS application implementation can be strongly automated. It causes a reduced time demand.
- ALS provides the measurement coordinates and the measurement density is very high.
- Ground point measurements in forested areas are more successful, since a ground point needs to be observed only once, while in photogrammetry two measurements are necessary for the coordinate determination. It is sufficient in ALS, if the laser pulse hits the ground from only one position, since the instrument measures polar coordinates.
- The laser instrument field of view is usually smaller than a camera aperture, so the occlusion caused by high objects is smaller.

The disadvantages of ALS should be mentioned here as well:

- ALS provides random measurements. The distribution of the measured points is determined by the scanning system.
- ALS provides unstructured measurements. However structures like building corner points or edges can only be measured at random, the high point density enables us to extract these structures.
- ALS do not provide spectral data. Photogrammetry provides images that makes easier the content recognition and understanding.

Because of the advantages and drawbacks of both techniques, they are not competitive, but complementary data acquisiton methods. The same data acquisition platform (aircraft) makes easy the simultaneous measurment and the fusion of the data.

2.2 Main principles of the technology

ALS is operated from an aircraft. It determines the distance between the instrument and a terrain point using a short pulse of light. The laser instrument emits an infrared laser pulse. A part of the pulse is reflected back from the surface and reaches the receiver part of the instrument. The laser measurements are distributed by the beam direction's deflection, which can be implemented by various scanning solutions. A time counter measures the time between the emission and the arrival. The travelled distance can be calculated easily from the speed of the light and the runtime. Sometimes more than one echo is reflected back from different objects (e.g. tree-crown and ground), that's why some of the instruments can detect the second or further echoes as well. The principle of laser scanner can be seen on figure 2.1. This figure shows the scanner, the units for position and orientation determination, and indicates some measured points on the surface.

For determining the coordinates of the measured point, the position and the orientation of the instrument must be known. The position is calculated from relative kinematic or differential GPS (Global Positioning System) measurements. It is composed of a reference station on a known location on the ground and a rover station on the aircraft. The orientation is determined by an INS (Inertial Navigation System). Direct georeferencing provides transformation of the measurements into a global coordinate system. The position of the laserhead and its orientation are known, so taking these measurements into consideration, the surface point coordinates can be calculated with a vertical accuracy of ± 10cm and the horizontal accuracy of $\pm 30 - 50$cm.

2.2.1 The main components of ALS systems

The system components belong to three main divisions:

1. range measurement and scanner units
2. units for position and orientation determination
3. data storage and control units

The laser transmitter and receiver unit belongs to the first division as well as the scanner unit that is responsible for measurement distribution. Usually these units are built together. The instruments of the second division determine the actual position and orientation of the scanner.

Range measurement by laser

Laser is a coherent, monochromatic ray of light. Therefore, it can have high intensity, slight beam divergence and a high frequency, which enables a high signal power and reflection perceptibility.

Two kinds of range measurement principle are possible:

- phase difference measurement
- runtime measurement

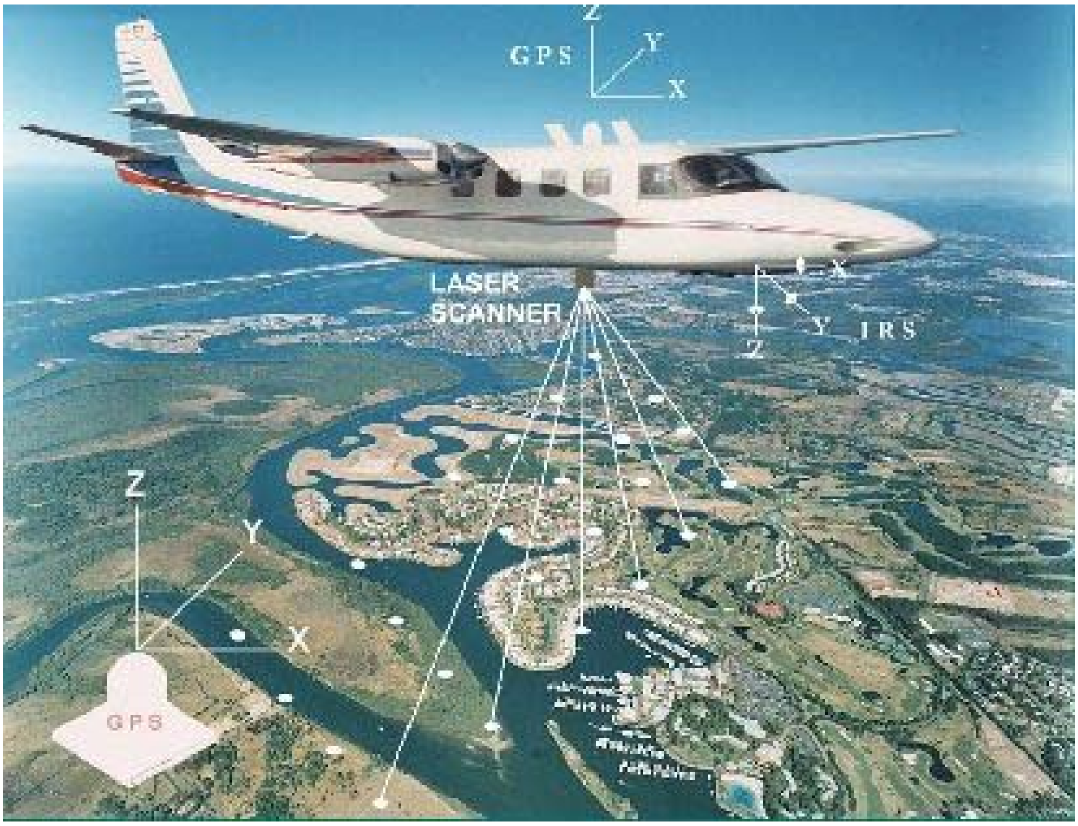


Figure 2.1: ALS principle (www.airbornelasermapping.com)

The first principle is based on the phase difference of the continuous wave (CW) laser ray, similar to the electronic distance measurement systems in surveying. This system operates with a long wavelength (~300m) and compares the wave phases of the emitted and received signal. The phase difference is proportional to the travelling time. Because this principle requires very high energy, only one commercial system (ScaLars, University of Stuttgart) works in this way, therefore it is only mentioned in this work. By the runtime measurement method, the transmitter emits a short laser pulse, which has a 5 to 12 ns pulsewidth and its wavelength is between 800 and 1600 nm, which is in the near infrared part of the spectrum. The pulse transmitting repetition shows the emitted number of pulses (*pulse rate*) and it is usually between 10 and 100 kHz depending on the system and the travel time. The sensing instrument can not separate the incoming echoes from different emitted pulses, therefore always only one pulse is on the way. This limits the flying height by high pulse rate. Objects in traveling direction reflect partly back the light that is detected by the receiver unit. From the measured travelling time, the distance between scanner and reflecting area can be computed. The maximum reachable measurement accuracy depends on the range measurement accuracy and the accuracy of the position and orientation provider instrument's which is typically $\pm 3 - 5cm$ nowadays.

Scanning

The scanner system determines the measurement patterns on the ground. Various scanning mechanisms are developed and applied in the systems:

- oscillating mirror scanner
- rotating polygon scanner
- nutating mirror scanner
- fiber scanner

Oscillating mirror scanners produce a zigzag line scan pattern, therefore the point homogeneity is not constant, at the boundaries of a strip, it is the most inhomogeneous. The most homogeneous point distribution is provided by the *rotating polygon scanner*. This unidirectional scan system provides a parallel line scan pattern. *Nutating mirror scanners* produce almost an elliptical scan pattern. According to the double scan, almost non occlusion occurs in flying direction (see figure 2.2). *Fiber scanner* of the TopoSys GmbH (Falcon) uses 127 optical fibers in one row to distribute and receive laser pulses. The relative few measurements in one row cause narrow strips, small aperture and a very inhomogeneous point distribution. This distribution is improved by an alternating movement of the scanner to the flying direction, which results in sinusoidal scan lines.
The point distribution and density affects the processing, since not all of the methods are independent of these data features. The point density depends on the flying height, scanning frequency, scanner aperture, flying speed and the measuring frequency. The flying height can vary from 100 m up to 3 km depending on the application and aircraft type. Flying speed is typically about 40-90 km/h in the case of helicopters and 160-350 km/h in the case of airplanes. Scanner aperture is between 10° and 60° depending on the system, but in some systems it is variable. Depending on these components, distance between measurements on the surface can be varied from 0,1 m up to some meters.

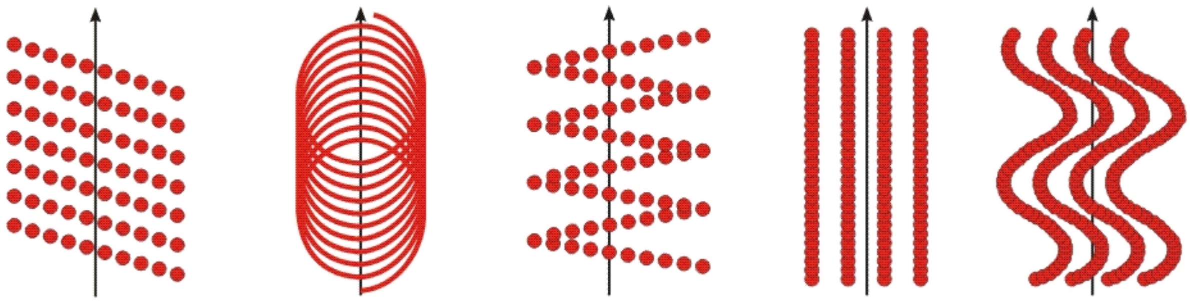


Figure 2.2: Footprints of scanning systems (rotating polygon, nutating mirror, rotating mirror, fiber, fiber with swing mode)(Steinle, 2005)

Positioning and Orientation

The global positioning system (GPS) can provide absolute positioning data for the aircraft every second. Highest accuracy can be reached with differential GPS (dGPS) measurements. The INS or IMU instruments provide orientation of the scanner with 100-400 Hz. Since the pulse repetition is much higher than the frequency of position and orientation measurements, the position and orientation data are interpolated in every moment between the real measurements.
A more detailed overview about system components can be seen in (Schenk and Csatho, 2001).

Scan angle	0-60°
Pulse rate	5-125 kHz
Scanning mode	Rotating poligon, rotating mirror nutating mirror, fiber
Scan frequency	10-65 Hz
Pulse width	5-12 nm
Wavelength	800-1560 nm
Number of recorded echoes	1-5
Beam divergence	0,3-2 mrad
Flying height	50-3000 m
Flying speed	40-350 km/h

Table 2.1: The range of possible properties of a pulsed ALS system

In consequence of the beam divergence, the footprint, namely the laser beam diameter on the ground may be 20-80 cm large depending on the flying height. Therefore smaller objects only partially backscatter the laser light. The receiver unit can detect an echo that has a higher energy than a certain threshold. From the detectable echoes, most systems record the first and last one, however in forested areas sometimes 4-5 reflections could be detected. There are commercial systems on the market now, which are able to record up to 4-5 echoes (e.g. ALTM 3100 by Optech, ALS50 by Leica).
The relatively large footprint leads to another "consequence". The laser beam has a cone form and its section with a flat surface is elliptical. This ellipse can be approximated by a circle. The size of the footprint shows that, however, the laser measurement is referred to as spot-wise, identified by 3 coordinates - it actually contains surface-wise information. Therefore in the data recording, information will be lost and it is not possible to find out, exactly which object is measured within the cone. Wherever the reflection place is located within the cone, it is considered to be in the centre axis of the cone. This means, a certain inaccuracy may affect the horizontal coordinates and small and low objects can be hardly measured by this technology.

ALS systems are usually able to measure and record the amplitude of the reflected pulse as well. This intensity of the reflectance among others depends on the size and surface material of the reflecting object (Katzenbeisser, 2003). Homogeneous objects have homogeneous intensity measurements - supposedly. Therefore, intensity data is also tested in the classification process (see chapter 6.4.2).

In modern systems, additional sensors can be found as well for acquisition of spectral information, like RGB camera (e.g. ALS50 by Leica), video (e.g. FLI-Map by Fugro-Inpark) or RGB/NIR line scanner (e.g. Toposys Falcon II). This additional information can complete the geometrical information of the laser scanner and can be used in several applications for analysis and visualization.

Another type of laser system has to be mentioned as well, which uses green laser that is able to penetrate into water and is reflected back by the sea bed. These bathymetrical laser scanners usually apply a dual system. The green laser measures the underwater topography and the infrared laser measures the topography above the water surface. The SHOALS system of the Optech company (Optech, 2005) has 40-50 m maximum penetration depth in clear water and less than 20m in turbid inland water.

More detailed information about the principles and technical specifications can be found in Wehr and Lohr (1999), Baltsavias (1999) and Katzenbeisser (2003).

2.2.2 Future trends

The fast development of computer storage speed and capacity as well as that of the processing speed has enabled us the so called full waveform scanners to be on the market since 2004. These systems are already able to detect not only a few echoes, but to digitize the full waveform of the reflected echo (Wagner et al 2004). In 2005 already 5 companies offer full waveform ALS systems (Riegl LMS-Q560, Litemapper 5600, ALTM 3100, Topeye II, Toposys Falcon III), which clearly outlines the future developments. These systems can be prosperous in applications, where vegetation mapping may be the central point (Blair et al. 1999). In urban areas the full waveform analysis may provide solutions for a more accurate sub-pixel edge detection method as well (Jutzi et al. 2005). System providers aim to decrease the beam divergence, which causes smaller illuminated areas and a reduced number of multiple returns. On the one hand, the energy loss during the reflections is lower and, therefore, the intensity of the echoes may not be as noisy as in current ALS systems. On the other hand, this causes the smaller footprint to hit the point and line-wise objects, like power lines with lower probability. To solve this problem, the Optech company developed a system (ALTM 3100) with dual beam divergence, which allows us to select beam divergence from two values according to the application purposes. These developments probably enhance the reliability of intensity data and therefore provides valuable additional data to the geometrical data.

In Toth (2004), 3 new methods for increasing the pulse rate are described. Nowadays, only one pulse travels at the same time, because the receiver can not identify multiple backscattered pulses. It is only possible, when the distance of the sensor and the ground is known, what is in fact the main goal of the measurement. Since the length of a backscattered pulse is less than 1% of the measured distance, more pulses could travel simultaneously. If the average sensor ground distance is measured with a single signal, than the instrument can change to interleaved mode and can emit more (4-5) pulses simultaneously.
Another interesting method for increasing the measurement rate is to use a dual system. This means that 2-3 different wavelengths are emitted simultaneously by a multiple wavelength output. Due to the different wavelengths, the pulses may use the same optical system and the receiver part can also separate the pulses.
The third new sensor type in Toth (2004) is the flash sensor system. The development of focal plane array laser systems is supported by military demand. Dense measurements that penetrate the canopy, support the recognition of military vehicles under trees by shape. The sensor is a 2D (128x128) receiver sensor array. A single laser shot is emitted and the receiver senses the echo like a digital camera, providing a 3D image. The challenge is to transmit and store a so huge amount of data, as well as the relative high signal to noise ratio (SNR), which is caused by the sensor elements sharing the weak energy of the sensed pulse.

2.3 Airborne laser scanner applications

ALS has become a common surveying tool in many applications. Some of them are presented here, I am not interested in describe all of the processes involved, just to show the wide scale of application possibilities.

Topographic mapping

The first and main application of ALS is the extraction of topographical surfaces. It is able to determine the ground elevation of the terrain, even in forested areas. High point density and measurement accuracy as well as short data acquisition time makes it superior than other traditional techniques (Kraus et al., 1998, Lohr, 1998).

Hydrology and flood plain mapping

Flood mapping, water management: by rapid mapping, flooded areas and non-flooded areas can be separated. More detailed, up-to-date DTM can be used for flood prediction, generated from high density measurements. The classification of objects on the earth's surface, like buildings and vegetation can provide information for the estimation of the parameters of runoff. Erosion of coastal zones can be monitored from multitemporal data as well (Brügelman et al. 2004).

Building reconstruction and city models

Building models generated from laser data can offer a basis for many applications. The reachable geometrical quality enables the use of the city models as a basis for optimizing telecommunication antennas, for urban planning, for virtual city models or even for positioning photovoltaic cells (Weidner, 1997, Vosselman and Dijkmann, 2001 , Hofmann et al., 2002 ,Vögtle and Steinle, 2004, Rottensteiner et al., 2005).

Disaster management

Using multitemporal ALS data, monitoring of changes can be carried out after natural or man-made hazards. Building damage can be detected and surveyed, providing information about the extent of damage for the rescue teams e.g. after strong earthquakes or as an extreme example after the terrorist attack against the World Trade Center in 2001 (Steinle and Bähr, 2002, Bähr et al., 2004).

Forestry

ALS applications in the field of forestry aims to determine forest and tree parameters. These can be the forest canopy mapping, timber volume estimation, biomass estimation, single tree segmentation and tree height, extent and shape estimation. Multitemporal data can be used for forest growth estimation and for forest stand monitoring (Hyppa et al. 2001, Nässet 2002, Morsdorf 2003).

Corridor mapping

Laser scanners mounted on a helicopter that flies at a low speed can provide data for several engineering applications like pipe line or power line surveying, railroad and highway mapping. Usually, the acquired laser data can be supplemented with spectral data as well. Due to the low flying altitude, clouds usually do not hinder the surveying (FLI-MAP).

2.4 Data structures and topographic models

Importance of topographic models in many engineering applications is highlighted in the previous section. Data for topographic modelling can be acquired by a wide range of measuring techniques. Terrestrial and airborne measurements provide topographical information about the earth's surface in various scales, sampling density and accuracy. Terrestrial measurements (e.g. tachymetrical) are time consuming, but very accurate, therefore, they can provide data economically only about small areas. Contrarily, airborne applications can provide high point density, with usually lower accuracy in very short time. Sampling density plays an important role in respect to the models' detailedness. A continuous surface, generated from this huge amount of data, is considered as a model of the surveyed topographical surface. Models can be described and handled by different data structures.

Regular and irregular data structures are the two main divisions. These structures and the various topographical models are described in this chapter.

2.4.1 Data structures

Data structures based on point cloud

The characteristic of ALS is able to sample the surface randomly, therefore, the measurements are not organized regularly, the points can be determined with their 3 coordinates in a reference system. Measurements constitute therefore a point cloud in a 3D space. To preserve primary observations, point cloud based surfaces should be used. Triangulated irregular network (TIN) represents the surface with a set of contiguous, non overlapping triangles. Each triangle facet is defined by three vertices and three edges. Within a triangle, the surface is usually considered as a plain. In this way, actually the original measurements constitute the surface.
Edges of triangles are generated on the basis of the point cloud. Not only one triangulation solution can be extracted on a certain point cloud, different criteria can manage the triangulation process. The most common method is the Delaunay Triangulation, where points are connected by edges so that no other points are within the triangle borders and the surface normals are minimized. The first criteria maximizes the smallest angle in the triangle, the second ensures the smoothness of surface.
In most cases triangles are considered as plains, therefore, points within triangles can be interpolated linearly within the 3 vertices. In this case, planar patches do not give precise approximation of the surface, another approach should be used to compute a small curved surface on the triangle domain (see Pfeifer (2002)).
TIN structure is able to represent the surface in 3D, which is favourable considering the characteristics of ALS data.

Data structures based on regular grid data

There are two common possibilities to store data in a regular grid. One is the raster structure, where the surface is covered with equally large rectangular cells. Each cell includes only one height value, which is referred to as the height of the whole cell. However, other regular tessellations exist as well, like regular triangles or hexagons, they are not widely applied for terrain surface description.
The other regular structure is the grid structure, which is very similar to the raster structure. Heights are stored in the grid nodes, which are located in regular grid so that their planimetric coordinates are equal to the grid coordinates.
Raster and grid structures are so similar that only the raster will be described here. The only difference is that in the grid the nodes, in the raster the raster center have the height information. Conversion between them is very easy; grid node is the center of the corresponding raster element.
Raster and grid can represent the surface in 2,5D that means, third dimension, namely, the vertical is a function of the planimetric coordinates.

$$z = f(x, y) \tag{2.1}$$

However it is a correct assumption in the case of bare earth, but it does not reflect the characteristics of laser scanner data. Since the laser beam is not vertical in every moment, vertical walls may be acquired, or even points can be measured on a bridge and exactly under the bridge on the ground with the same planimetric coordinates.
Progressive sampling offers a grid based data structure, which stores data in a quad-tree structure.

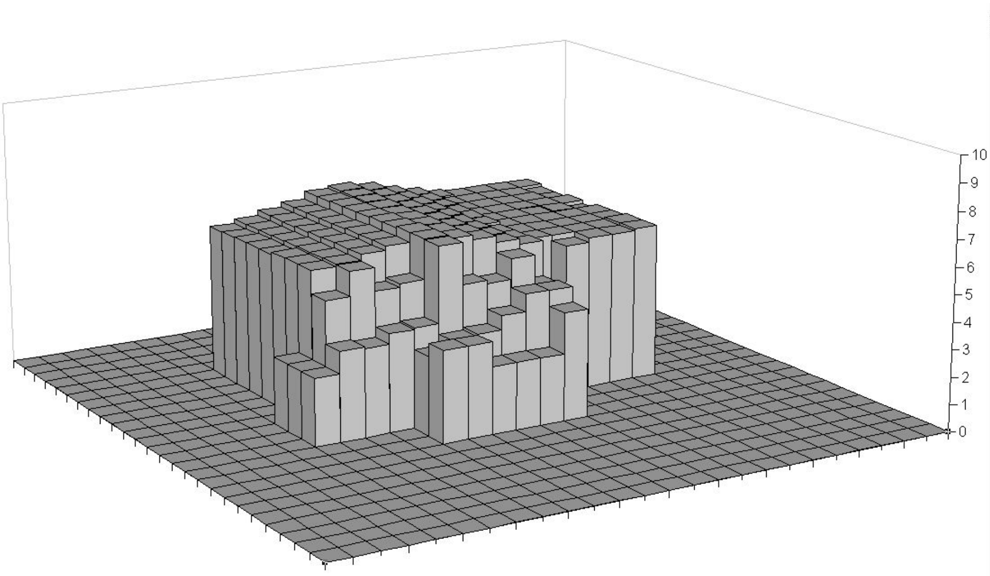


Figure 2.3: Raster data

Interpolation

Measuring all the points' location and height in the area of interest is usually difficult and expensive. However ALS provides very high point density, samples do not meet with all desired points. To extract heights in arbitrary locations, interpolation is necessary from given measurements.
Interpolation process in city areas requires other demands than in vegetated areas. Step edges should be preserved, because they are important characteristics of topography. Smooth transitions on other locations are still necessary, therefore an edge preserving interpolation method should be used. In this case, height difference between neighbouring points participating in the interpolation pass over a certain threshold, the current point's height is set either to the highest or to the lowest neighbouring point height. Taking the maximum value, it results in a slight growing of the objects (e.g. buildings), while taking the lowest value causes a shortening of object extension. Where the height differences between the neighboring points are below the threshold, a standard method can be used,

therefore, terrain smoothness can be guaranteed. It causes on the other hand the border lines of buildings to be not perfectly straight.

Point cloud vs. raster data

In ALS applications both structures are used comprehensively. Some systems and application solutions are based on the raster structure, others on the point cloud. Data storage and processing systems have not been standardized, therefore, a lot of solutions exist and probably will be applied also in the future. Some process developers use raster data, because its advantages are favoured, but on the other hand, some developers are committed to point cloud and TIN. However TIN models have a better ability to describe precisely the surface, but, because TIN is based on the original points, it can not be smoothed. Raster has a smoother, more natural appearance and, for this reason raster is used usually for visualisation, even if the computation uses the original point cloud. In TIN structure, the point density is variable, while in raster it is fixed. Due to the regular structure, simple computation processes can be used on raster and more complicated algorithms are necessary in the case of TIN.
TIN structure is able to represent 3D models, while raster is limited to 2,5D. 3D models are important to represent surface overhangs. These surface elements can be described in raster data only with geometrical restrictions. Both data structure can be converted easily to the other. Raster heights can be interpolated and stored within triangles in TIN structure. In raster to TIN conversion, each raster may be considered as a node point in the triangulation.

Hybrid structures

As we can see, both data structure types have advantages and disadvantages. Raster data is more convenient in order to handle surface wise information, while point cloud can better deal with point and line wise information. Raster data can be processed more simply and faster, while TIN structure uses the raw measurements in the processing. In order to combine advantages of the different structures, hybrid structures can be used as well. Hybrid systems are able to store surface wise data in raster format and point and line wise information with exact coordinates. Although, these systems compound advantages of different structures, naturally they can not eliminate their drawbacks.

2.4.2 Topographical models

Models are representations of physical objects. They are used in engineering to test a phenomenon of a physical object. Abstract models are used for the theoretical modelling of a phenomenon. In ALS based applications, models represent the topographical surface. As the measurements represent the surface in discrete points and not in continuous surfaces,

these models are not the perfect representations of the physical surface.
Digital topographical models are defined in Kraus (2000) as simplifications of the real topography that are created through idealisation and discretisation and that are prepared for electronic data processing.
According to the DIN standard (DIN, 1998), digital elevation models (DEM) are a mass of digitally stored elevations from regularly or irregularly distributed points, which gives an adequate representation of an object's height structure. In ALS applications, mostly digital terrain and surface models (DTM and DSM) are used.

Digital surface model

ALS measures in first pulse mode the top of the visible surface, which means, backscattered echoes are recorded not only from terrain but also from objects. First echoes are reflected back by the top layer of the vegetation canopy, by building roofs, vehicles, power lines and even by human beings. These objects can be represented as a surface, which is called digital surface model (DSM).
DSM is widely used in various applications, where all objects on the terrain surface play an important role or the acquired object itself is the subject of the investigations. These are e.g. the forest management, city modelling, flood mapping or corridor mapping.
Surface models can be extracted not only from first echoes (figure 2.4 left), but also from last echoes (figure 2.4 right). Last pulse surface models include objects that are illuminated by the laser and backscatter the whole remaining pulse. These objects are e.g. buildings, part of vegetation and larger vehicles.
Additionally, we distinguish summer and winter surface models, which terms imply to the season of data acquisition. Since the natural cover differs significantly in these seasons, first and last pulse DSMs are also different, depending on the data acquisition date, therefore we can distinguish between winter first- and last- as well as summer first- and last pulse DSMs. The various natural covers influence the vegetation detection process as well.

Digital terrain model

Digital terrain models describe the surface of earth without artificial and natural objects, like buildings, vehicles, or vegetation. DTM are defined as smooth surfaces, but structure lines and points should be taken into consideration. A general precise description of DTM is not identical always, since in some cases, certain objects may belong either to the terrain or to the objects. Roads in cities are the typical examples, since terrain can be the solid ground under the road, or the covered road itself.
Bridges can be defined either as part of the DTM or as an object that does not belong to the terrain. In some cases the term '*terrain objects*' are also defined, which can be e.g. huge rocks on the surface.
Smoothness can be defined as the continuity of the first derivatives (Pfeifer, 2002). Using

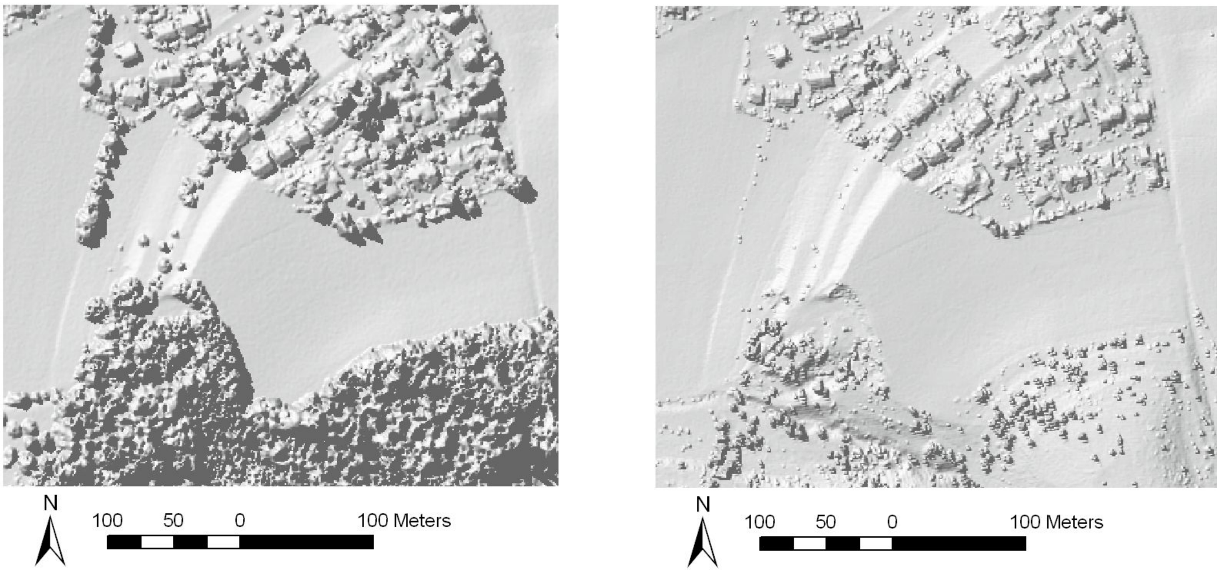


Figure 2.4: First pulse DSM on the left and last pulse DSM on the right.

planar patches, discontinuity of first derivatives may occur along the triangle edges.

Structure and break lines are very important in the description of the surface, since they effect sudden changes in the terrain's run. Direction of normal vectors on the two sides of break lines are different, the surface smoothness (continuity of first derivatives) is refracted. Break lines change the criterion of triangulation, while triangle facets must not overlap break lines. Due to this, triangle edges should be defined by the break line, even if the generated triangles are not optimal. ALS data gathering is not controlled by a human operator, therefore, these structures can not be measured directly. A common error source in the filtering of ALS data is that points are filtered out in the environment of these lines, therefore, the terrain characteristic changes significantly. The ISPRS filter test shows this problem (Sithole and Vosselman 2003). To avoid this phenomenon, Briese (2004) proposes break line detection and their use as an additional filter condition. Segment based filters may also bridge this problem, since homogeneous terrain segments are usually limited by break lines and ridges. A TIN based DTM can be seen on figure 2.5.
In ALS applications, a DTM can be generated from last pulse DSM. This extraction process, which selects the ground points, is called filtering.

Normalized digital surface model

Normalized digital surface models are derived from a DTM and DSM, i.e. it can be generated by subtraction the DTM from the DSM:

$$nDSM(x, y) = DSM(x, y) - DTM(x, y) \tag{2.2}$$

It means that the influence of topography on heights are excluded from the surface model. It contains all objects on the terrain surface, in an ideal case only the objects without any terrain influence. Since the heights are derived from a DTM, the inaccuracy - which is originated from the filtering and interpolation errors - appears in the nDSM as well. According to the DSM basis, first and last pulse nDSM can be distinguished (figure 2.6).

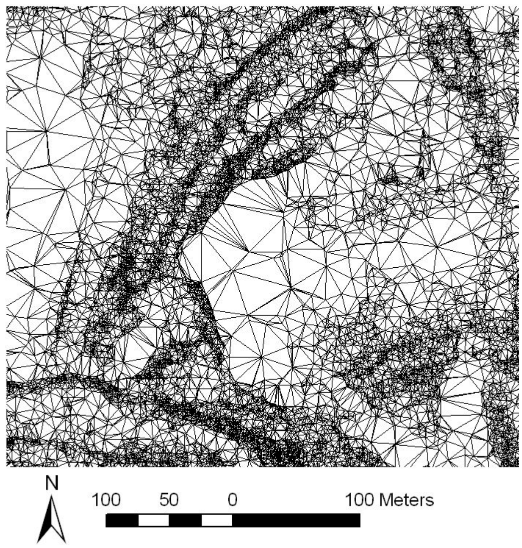


Figure 2.5: TIN based DTM

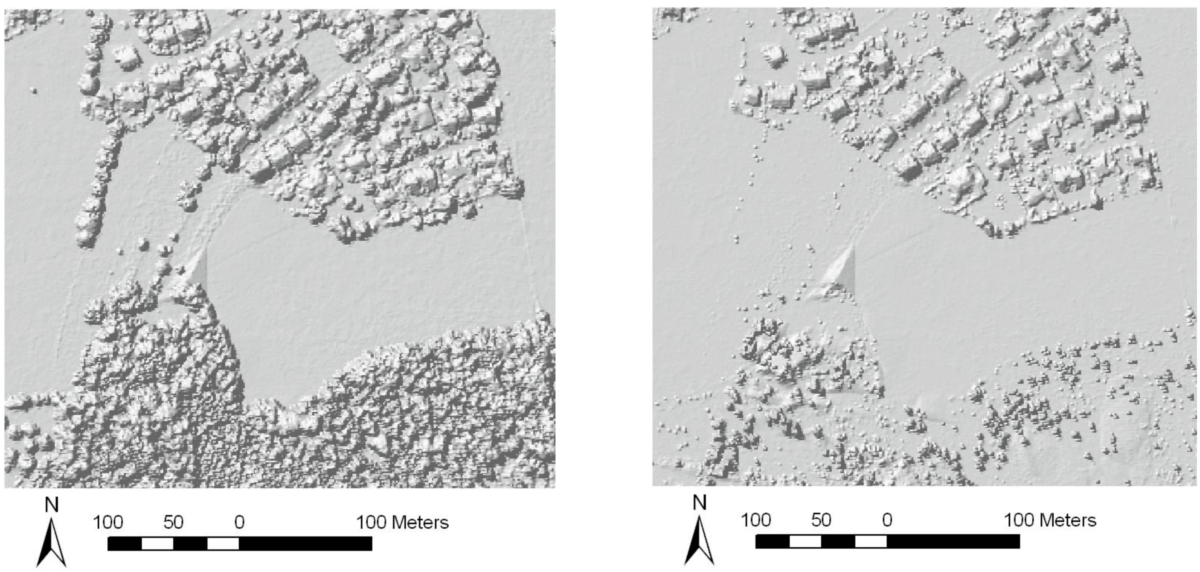


Figure 2.6: First pulse nDSM on the left side and last pulse nDSM on the right. It does not contain the influence of the topography (compare to 2.4). The complete vegetation can be observed on the first pulse nDSM, but only the partial vegetation on the last pulse nDSM.

Chapter 3

Methodology of classification

Before the presentation of the approaches, some important terms, which occur frequently hereinafter, should be defined. Additionally, these terms have to be described briefly due to their meaning in this work.
In the second part of this chapter, the frame of the new laser scanner data classification method is presented shortly.

3.1 Definitions

Classification

Classification is a very general term and means assigning unknown samples to well defined classes (Bähr, 2005).
The task of a classifier component of a pattern classification system is to use the feature vector provided by the feature extractor to assign the object to a category (Duda et al.,2001). The feature extractor reduces the data of a single segment by measuring certain "features" or "properties".
In remote sensing, classification is divided into two main groups. In the *supervised classification*, the human operator defines the classes before the process. In computer vision *knowledge based system* are mentioned. In the *unsupervised classification*, the classes are defined automatically during the procedure without human intervention. This is in fact not classification but segmentation, since the classes are not defined apriori and the classification happens in a further step, when class names are assigned to the segments.
In this work *object classification* is the supervised classification of segmented objects with regard to their geometrical, radiometrical, and other features.

Filtering

Generally, filtering is the separation between the required and unrequired information. In the digital image processing, neighbourhood operations are also called as filters. "They extract a certain feature of interest from an image" (Jähne, 2002). The task of separation of ground and non-ground points is called filtering in the field of ALS. It can be considered as a supervised classification of measurements into two classes, or as the labelling of measurements as terrain or object points. In the literature, this term's definition remains on the whole the same: and will mean the same in this thesis as well.

Segmentation

According to Jähne (Jähne, 2002), regions of constant features and discontinuities are identified by segmentation. In Bähr (2005), segmentation is defined as the creation of homogeneous sub-regions of a scene. Homogeneity may refer to different features, like spectral signature, texture, size or shape of samples. Segments are aggregated by connecting areas on the basis of common properties.
In Duda et al. (2001), segmentation operation is used in which images of different objects of interest are somehow isolated from one another and from the background.
Segmentation is a technique that splits a model up into regions, which properties differ from those of their neighbours. It can be achieved in two ways, by identifying the segment borders (edge detection) or identifying the segment area (region growing).
In this work *segmentation* is the indexing of point groups that belong geometrically to a continuous surface. *Object segmentation* is the separation and indexing of point groups that belong to the same 3D object, which is significantly higher than a smooth terrain surface approximation. However 'significantly higher' and 'surface approximation' are not absolutely definable terms. These objects are buildings, vegetation, or terrain parts in those areas where the run of terrain surface changes suddenly (e.g. in the neighbourhood of breaklines).

In this thesis, the sequence of descriptions starting from filtering to segmentation and classification shows the development of ALS data processing. First, methods for the separation of terrain and non-terrain points are developed. Than it became more important to build segments and to extract attribute information from the points. Although the new generation of filters are based on segments, segmentation processes will be presented after filtering.

3.2 Method framework

In this research the following classification method has been developed. The single steps of the process are not described in the same chapter. Every single step is discussed together with the existing methods from the literature that have the same purposes. So, for example the filter step is presented at the filter methods, in this way the existing and new methods are comparable. The new approach in this thesis classifies the points by 2 main procedures:

- filtering of ground points

- classification of objects

These main procedures can be derived into 6 steps, so the process of classification of terrain points, buildings and vegetation are applied as follows:

1. segmentation of last pulse data (chapter 5.3.1)
2. selection of terrain segments (chapter 4.1.6)
3. normalized DSM extraction (chapter 2.4.2)
4. object segmentation (chapter 5.4)
5. object classification (chapter 6.3)
6. vegetation detection (chapter 6.7)

The aim of the 1^{st} step is to build homogeneous ground and homogeneous object segments. The last pulse measurements are segmented in order to provide homogeneous segments in respect of the classes of segmented points. The main goal of this segmentation is to build homogeneous terrain segments. It is assumed that the terrain is locally smooth, outliers are not part of the ground. Naturally, not only ground segments have smooth surface, thus non-terrain segments (e.g. roofs) are shown in the results as well.

In the next step, the selection of ground segments is applied. Terrain segments are detected by a segment based robust interpolation method, which uses a rough approximation of the terrain surface to select them in subsequent iteration steps. As a result of the process, the ground points are separated from the rest.

For the building and vegetation classification, a normalized DSM (nDSM) is generated. In this special DSM, the influence of terrain is excluded. It contains only objects upon the terrain surface.

This nDSM provides the basis for an object segmentation method. Points of each object are bound together by a region growing segmentation method. These segments are larger objects, like buildings and trees. In case the filtering was not perfect and larger terrain parts remain in the nDSM, these may be segmented as well. These are called terrain objects.

These segmented objects can be classified by a statistical method (maximum-likelihood) or by fuzzy logic. Both processes need so called segment features that describe each segment by miscellaneous properties, like shape, surface smoothness etc. The classification results buildings, vegetation and possibly also terrain objects. Since the last pulse data does not contain the whole of the vegetation, the rest of the vegetation should be detected in the next step.

First and last pulse differences offers a possibility to detect vegetation, building walls, power lines and smaller objects, like vehicles. Buildings and their boundaries can be masked out inside and around the classified buildings. Power lines and small objects can be eliminated by morphological filters. The rest of first and last pulse differences indicates vegetation.

Chapter 4

Filtering

The selection process of ground measurements in ALS data is called filtering. The aim of this application is to generate digital terrain models. Since the start of commercial utilization of this technique, filtering is one of the most important applications in ALS data processing. This statement can be demonstrated by the high number of existing methods.
In this chapter, a short overview of some selected methods is given and a new way of *approach systematisation* is presented. The purpose of this new system is to show the further development possibilities for a new generation of filter approaches.

4.1 Filtering algorithms

4.1.1 Morphological filters

One of the first filter methods is based on the operators of mathematical grey value morphology (Lindenberger (1993), Weidner & Förstner (1995), which is known from the digital image processing (Haralick et.al (1987)). This allows us to process with slight modifications not only rasterised data, but point clouds as well.
Lindenberger (1993) proposes a method, where the lowest point within a moving window is taken to estimate a rough surface. Points are filtered out that have a height difference exceeding a defined threshold. The relative large window size is decreasing by iteration. The results depend on the window size and on the allowed threshold.
The process of Weidner and Förstner (1995) begins with a morphological operation called *'opening'* that provides an approximation of the terrain surface. A more robust method against measurement errors can be seen in Eckstein and Munkelt (1995) and in Lohmann et al. (2000). This dual rank filter uses k% and 100-k% quantils in the opening instead of minimum and maximum values.

$$\bar{\bar{z}} = (z \ominus_k w) \oplus_k w \tag{4.1}$$

,where
$\ominus_k$ - erosion
$\oplus_k$ - dilatation
w - structuring element

The size of the processing window can be estimated upon a-priori knowledge of the size of the largest object. To solve this problem - i.e. the a-priori knowledge of the structuring element -, **Schiewe** (2000) proposes a so called compressing opening method, where in a first step every piece of the processing area is filtered with a very large and with a very small window size. The results are compared and in cases where the differences between them are too big, the window sizes are changed in an iterative process. The iteration stops, when the surfaces - extracted by the different window sizes - do not differ significantly.

The advantage of morphological filters is the short processing time and that they use relative few parameters, therefore they are quite easy to manage. On the other hand, they need relative accurate a-priori knowledge about the characteristics of the topography. The quality of the results is unsatisfactory in complicated scenes, where extremely different object sizes and topographical structures exist. In some cases manual intervention is necessary to limit the processing area in order to avoid loosing important terrain structures.

The slope based filter in **Vosselman** (2000) uses mathematical morphology as well. It approximates the topography of the terrain locally, using a structuring element. The structuring element defines the maximum acceptable height difference between two points with respect to their distance. All points below the structuring element are accepted as ground points and all points above it are identified as object points. For each point, the structuring element and original heights are compared. The height difference between the neighbouring points depends on the topography as well, points on steep slopes are usually rejected. When higher elevation differences are accepted, object points also remain in the data.

The adaptive slope based filter from **Sithole and Vosselman** is an improved variant of the previous algorithm. This method improves the performance of the filter on slopes. The structuring element is not the same at every point, as in Vosselman's filter, but it is adapted to the steepness of the slope. A rough surface is approximated through points that are selected as the lowest points in a regular grid over the area. With the help of this approximated surface, local slopes can be computed at every point. Considering these local slopes, the local structuring elements will be determined. In what follows, the algorithm runs with the local structuring elements as the slope based filter.

Roggero developed a method, which works on a similar way as Vosselman's slope based method. The threshold of the slope criterion is adapted to the slope. A rough surface is estimated first using a local regression criterion that also considers the local variance of the data. Algorithm calculates the minimum height in a local operator. It is assumed that points far from the minimum have less effect on the local slope, therefore the points are weighted according to their distance and height difference. Using the distance and height difference from the minimum, a regression plane is estimated and a maximum height difference from the regression line is computed according to the distance from the minimum point. The data are classified by the vertical distance from the rough terrain model. Using two thresholds, points are classified as ground or non ground points, but between these classes the points are non classified.

Wack and Wimmer (2002) developed also a morphological filter that is based on raster structure. The method works in a hierarchical way, where first a 9m large raster is generated and the 1% quantile of the heights are taken as the raster element's elevation in order to take the lowest ground point and filter out the negative gross errors. After this step, on the rough terrain, only the large buildings and densely vegetated areas may remain. These objects are eliminated by a Laplace filter in the next step. On the basis of this 9m raster, a 3m raster is computed from the original points. The heights of the raster elements are taken when the height difference between the 9m raster and the point is within a certain threshold. In those raster elements, where no terrain points occur, the height is computed by a Laplacian filter again. The method continues the same way by raster densification using 1m raster size.

4.1.2 Region growing based filters

The edge based approach of **Brovelli** (2002) assumes that closed boundaries limit objects. The process works on raster basis. It detects and connects edges at the boundary between objects and ground. Since objects do not have closed edges by all means, after a region growing step the edges are connected and in case they are closed, they will be considered as objects. This method uses first and last pulse height difference as well.

The region growing based method of **Nardinocchi** (2003) applies height differences to get segments. The geometrical and topological description of the segments is the most important aspect. These can be presented with two graphs, on a set of rules and on a further segmentation, which is based on the orientation of height gradients. The segments are classified into three main classes: terrain, buildings and vegetation. Differences between first and last pulse heights are utilized in the vegetation classification.

4.1.3 TIN densification

This group of filters work progressively. Some points are identified as ground points and based on those, more and more points are classified as ground points. DTM generation using adaptive TIN-models are proposed by **Axelson** (1999). The surface is approximated with a coarse TIN, where the seed points are selected in a user defined grid. New points are added when they fulfil certain criteria concerning the relation of the points and the containing triangle. The parameters of these criteria are estimated from the data and the changes during the process. The iterative algorithm densifies the TIN, and recomputes the parameters after each iteration step. Points must be within a certain distance to the triangle and the angle between the triangles normal and the line from the point to the nearest nod must be over a threshold.

Von Hansen and Vögtle (1999) developed a so called convex concave hull approach. First, a convex hull is set upwards with the help of a triangulation method (e.g. Delaunay) to the data. In this process, the locally lowest points are selected, which are most probably ground points. These points are triangulated so that no points could lie below the triangles (see figure 4.1 left). For each triangle of the convex hull, new points will be added that are located within the triangle and fulfil certain criteria (figure 4.1 right). The simplest case is a vertical distance criterion between a new point and the triangle surface. The threshold depends on the size of the triangle, namely on its longest side. This function can be linear or non-linear. Other criteria can be applied as well, like maximum curvature. When a new point is accepted, the old triangle is divided and triangulated taking into account the new point. Triangles are densified until no additional points can be joined to them. This densification approximates in every step a more detailed terrain surface.

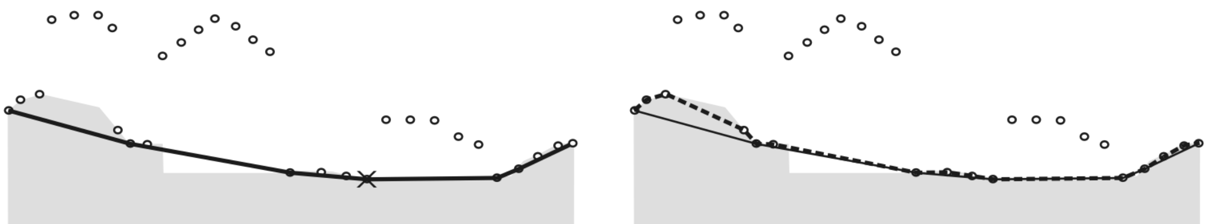


Figure 4.1: Convex concave hull approach. On the left: convex hull (line) is fitted on the data. On the right: convex hull densification by concave triangle nodes (dashed lines) [Steinle, 2005]

The method of **Sohn and Dowman** (2002) also generates terrain model by TIN densification. It fragments the entire terrain into a set of piecewise segments. All terrain segments are assumed to be plain. A criterion is defined to distinguish on- and off-terrain points. The two step densification starts with a downward densification. Corner points of the area are chosen and triangulated. Lowest points in the triangles are accepted as new points and the triangles are re-triangulated. This process is repeated until no points remain under the triangles. In the next step, an upward TIN densification process is performed in order to select the remaining bare earth points. In this process, new points over the triangles are accepted using tetrahedron models. A point belonging to the flattest tetrahedron is selected as a new point and the densification process is repeated.

The advantages of the triangulation based methods are the short runtime, the relative simple operation, with relative few operation parameters and its robustness. The disadvantage is the negative blunders which have a high impact on the surface, they shift it downwards.

4.1.4 Filters based on a surface model

In the algorithm of **Kraus, Pfeifer, Briese** (Kraus and Pfeifer (1998), Pfeifer and Briese(2001)) a robust interpolation method is used to classify the ground points. First, a rough approximation of the surface is computed. All the measurements are weighted according to their distance to the approximated surface. Ground points which are under or on the averaging surface get high weights (close to 1), therefore, they have a significant influence on the surface run, while objects points above the averaging surface get a lower weight (close to 0), therefore they have a small influence on the run of the new surface. After determining the weights, the surface is recomputed considering the new weight values. If the point to surface distance is too large, the point is eliminated from further calculations, so classification is also performed in this process. This iteration process is repeated until the surface is not changed or a maximum number of iterations are reached. The method works in a hierarchical way as well, which uses regular data pyramids on two or three levels. Firstly, a data set is created with a lower resolution. Then data are filtered with robust interpolation and a DTM is generated. In the last step, this DTM is compared with the points from a higher resolution and points are taken, which are within a certain distance to these. This process is repeated for each level. The hierarchical approach accelerates the filter process, makes it more robust and improves the elimination of large buildings and dense vegetation. The filter variant of robust interpolation by Briese uses break line information as well. The drawback of the approach is that it is controlled by relatively many parameters and sensitive to the negative errors.

The algorithm of **Elmquist** (2001) is based on the theory on active shape models (Cohen and Cohen 1993, Kaas et al, 1998), which originated from image processing, where it was used to detect contours. The ground surface is estimated by active shape models. The shape of an active contour is the solution that minimizes an energy function. This function contains, on the one hand, internal energy, which is described by physical characteristics like elasticity and rigidity, and on the other, hand the potential field that is given by the height data.

4.1.5 Filters based on segments

For these filters it is assumed that segments of objects are situated higher than the ground segments. **Sithole** (2004) introduces a method, which compares the neighbouring segment heights in different directions and based on a set of rules, each segment is classified as object or ground. Three directions are indicated on the data set, which is divided into equally wide profiles in all these directions. Points are connected into line segments in every profile, when they are on the same surface. The line segments from the 3 different directions are combined to build segments from the point cloud. This segmentation method is described in chapter 5.3.3. The macro object detection is based on the topology of the segments. Six different shapes are assumed, for example no shape; raised; lowered; high; low; and terraced according to the spatial proximity of the neighbouring segments. Objects and the bare earth have typical shapes that can be constituted with these 6 shapes. According to the topological relation of the neighbouring segments, a shape grade is computed for each segment. Each kind of shape is associated with the class 'bare earth', 'object' or both. The degree of association is a value between 0 and 1. The classification of segments is based on the determined shape grade and the association grade of a class. A class grade is determined so that it can be the weighted mean of the associations, where the weights are given by the corresponding shape grades. A segment is classified as an object, if the shape grade is equal or greater than a threshold.

The **eCognition** software is used to segment raster data with a region growing method. **Lohmann and Jacobsen** (2003) apply among others the compactness of these segments and the height difference to the neighbouring segments in order to detect different types of areas including terrain. In the method of **Schiewe** (2001), maximum and average gradients are used for classification of the data.

The method of **Lee** (2004) segments planar patches from the points with a region growing method. These patches are grouped into a set of surface clusters. It is assumed that the connected and continuous surface patches belong to the same object and that large vertical discontinuities usually do not exist between ground segments. The ground clusters are selected on the basis of the simple assumptions that objects are above the ground and ground clusters are relatively large.

4.1.6 Filters based on segment to surface model relation

The segment based robust interpolation method (**Tóvári and Pfeifer**, 2005) applies segment filtering based on their location over an adjusted surface. This new approach tries to exploit the advantages of point based and segment based filtering methods. It is presented here in detail, because it is used for terrain extraction in the classification approach in this thesis and it represents a new kind of approach. The quality assessment can be seen in chapter 7.

Robust interpolation for point groups

The method described in the following is an extension of the robust interpolation (4.1.4).

The most important novelty is the type of input data. While input data are points for the original process, the input for the extended robust interpolation is the results from segmentation: points from segment j with their 3D coordinates (x_i^j, y_i^j, z_i^j). Also an indicator c^j can be given, specifying if this segment should be subject to ground/object testing or not. In the latter case these points are considered to be ground beforehand. For example, the size of segments can be checked a-priori, if they reach a certain size. It is assumed that objects are limited in extent, but terrain segments can reach any extent. Additionally, a σ_0 a-priori has to be specified, which is the nominal laser measurement accuracy. ± 10 cm for the height accuracy is a suitable value in the case of ALS measurements.

During the iterative ground surface determination, instead of every point having its own weight, each point group has one weight w^j which applies to all points within the segment. Initially this weight is set to one, since no a-priori information exists about the segment's class.

The robust interpolation for point groups runs as follows:

1. A surface is interpolated for considering the points with their current weight w^j.
2. The filter values r_i of the interpolation are computed for each point and normalized by dividing with σ_0.
3. The filter values belonging to one segment are grouped and one representative filter value $r^{j'}$ is determined (averaging). Based on this value and a weight function (4.3) for robust adjustment, a new weight is set for the segment.
4. Test for iteration stops, if not, continues with step 1, otherwise classifies segments as ground or off terrain on the current value of w^j.

For computing the surface moving least squares (MLS) with a first order polynomial (a plane) is used. A 2-dimensional weight function is used to give points near the interpolation position higher weights, reaching a value of zero at a certain range. In the interpolation the weight from MLS and w^j is multiplied. Segments with a large w^j will, therefore, have a larger influence on the run of the surface. Segments with small or zero w^j have small or no influence at all. Two surfaces are presented in two different iterations in figure 4.2. The continuous line represents a surface in an earlier iteration, while the dotted line shows a surface in a later one. We can see that the non-symmetric weight function shifts the surface downwards.

The filter value is the signed distance of the interpolated surface to the observed point. It is positive for points above the surface, negative otherwise. Divided by the a-priori accuracy of the measurement system, $r_i' = r_i/\sigma_0$ yields a unit-less value. Depending on the distribution of measurement errors, points lying on the ground surface usually have values of r_i' from -2 to +2. Since these are normalized residuals, it means that within twice the standard deviation, the errors are accepted. Assuming normal distribution of the random measurement errors, 95% of the ground points are accepted and only 5% of the ground points with large but random measurement errors are eliminated.

As a segment is either entirely a ground point segment or entirely an object point segment, all normalized residuals of one group are analyzed together. Therefore, a representative normalized filter value $r^{j'}$ is computed for each segment from the normalized filter values belonging to the investigated segment. This is an average of all the single normalized residuals. However, the mean filter value is not the only one that can be taken. The median or any other quantile of the distribution, including the maximum positive filter value, can be used. In the examples, the 3rd quartile is taken as the average filter value.

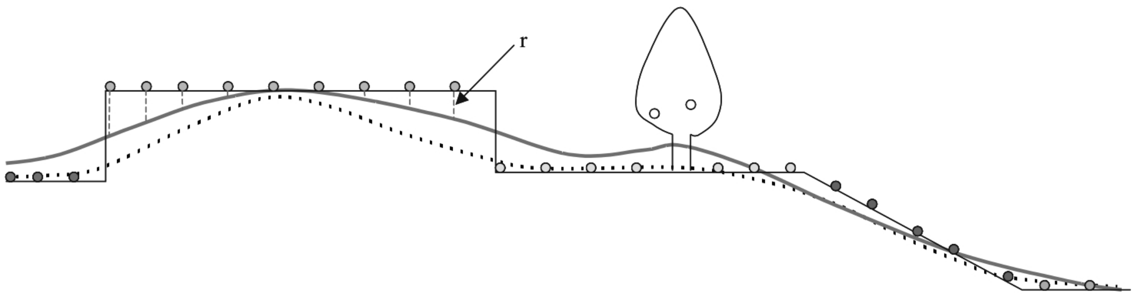


Figure 4.2: Segment based robust interpolation. The continuous line presents a trend surface in an early iteration, while dotted in a latter one. Points in the same greyscale belong to the same segment. Residuals to the trend surface are also shown at one segment.

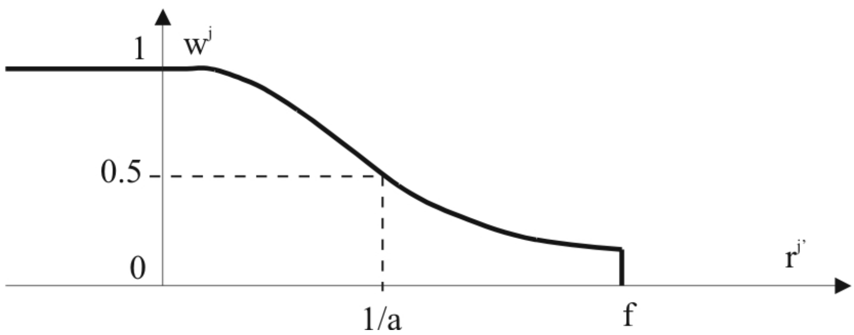


Figure 4.3: Parameters of the weight function. (Where w is the weight, a is the half weight filter value and f is the maximum filter value, where the weight is higher than 0.)

The function to assign a weight for the segment is the standard weight function from robust adjustment with one modification (see fig. 4.3). It is centered on the origin and drops from the maximum 1 to 0 for the right branch (positive filter values). The left branch yields a weight of 1 for all (negative) filter values, i.e. segments with an average filter value below 0, "below the surface" will always have the maximum weight. The weight function is cut off at the right branch and set to zero for filter values above a certain size (f). For values of $r^{j'}$ between 0 and f, the weight function takes the form $w^j = 1/(1 + (r^{j'}/a)2)$, where a is the so-called half-weight filter value, the argument where the weight function yields the value $1/2$. Parameters of the weight function (a and f) are detrmined empirically.

Iterations shall be stopped, if all representative residuals are either small (e.g. within -2 and +2), or very big (e.g. higher than 10). This means that the segments have been classified into ground (low residual) and object (high positive residual). The values chosen depend on the method of computing the residual. If, for example, the mean value of the individual residuals is taken as the representative, the ground segments can be expected to have a representative residual of zero. After the last iteration the segments are classified as terrain or object, depending on the value w^j.

Crosilla (2005) proposes a similar method to the previous one. In this case mixed nonparametric and parametric models are used for the segmentation.

In the paper of **Abo Akel et al.** (2005) an inverse approach of the segment filtering can be found. In contrast to the segmentation based robust interpolation, this approach first applies a rough filtering on the original dataset. The rough surface offers the seed points for a region growing based segmentation method. However, segmentation process works on the original dataset, according to the seed point selection, only the bare earth points are segmented. In this way, it can also be ensured that the break lines, embankments and ridges are completely preserved.

4.1.7 Filter features

Comparison

A perfect general solution of filtering has not been developed yet and this task is hardly realizable. Whereas a filter performs well on a certain kind of landscape, it may fail on another type of landscape. While one method may be better utilizable on a special type of landscape than another, the other may perform better on another type of landscape. Therefore an unambiguous numerical comparison of filter results is not easy and announcing the "best method" is impossible. Comparison of some major filter algorithms can be found in Sithole and Vosselman, (2003) and in Sithole (2005).

Errors in filtering

Filtering is a classification process, which classifies the points into two classes. Misclassification has therefore only two cases, so two kinds of errors can occur in the filtering process:

- type I errors are the eliminated ground points and
- type II errors are object points, which are not filtered out.

Type I errors occur typically on steep slopes and near break lines and ridges. It needs a lot of effort to correct it, therefore it is not economical in the industrial production. Type

II errors can be corrected manually more easily, since to remove a point is easier than to replace it. Usually the minimalisation of a type of error causes a rising number in other type of errors. Type I errors are not so conspicuous in most cases and most of the filters aspires to minimise type II errors, so they try to filter out as many object points as possible and, therefore, most of the errors are type I.

		Filter result	
		Terrain	Non-terrain
Ground truth	Terrain	Terrain points	Type I errors
	Non-terrain	Type II errors	Non-terrain points

Table 4.1: Type I and type II filtering errors

Typical error sources

All filtering methods have a basic concept, how terrain and object points can be distinguished from each other. Typical errors occur in the results, when the basic assumption of the filtering algorithm does not fit to the reality. All the assumptions fail in certain cases in reality, therefore a perfect solution of the problem is not realizable considering only one assumption. A complex method may provide more suitable results.
The quality of the data can affect the quality of the results as well. The point density has an impact on the detailedness of the surface, higher point density intensifies the effect of the small details, while low point density may lead to loss of details.
Data anisotropy occurs, when the measurement density is not constant in every horizontal direction. This means that in one data set the problem of varying detailedness may occur. This may effect especially filters that use geometrical point relations.

The possibility of very similar ground and non-ground objects requires the recognition of object classes. The difficulty of this task is shown by the fact that some objects are hardly recognizable on aerial photographs even for a human operator.

In industrial practice, from economical aspects such parameters like computation time, and number of parameters should be also considered.

Data in filtering process

Filtering algorithms use measurements either as a point cloud in original form with x,y,z coordinates, or in gridded form as a matrix. Methods that filter point clouds, usually simply remove object points from the dataset, while methods that filter raster data usually interpolate a new height for each object point, in order to close the terrain surface. ALS is a 3D measurement system and therefore original point clouds represent the data characteristics

better than raster data.
Most of the filters use only last pulse data. First pulse measurements do not contain any information about the associated last pulse data, therefore the usage of them in filtering is unnecessary. In the case, a first pulse measurement is backscattered by a tree crown, the corresponding last pulse measurement may be reflected back by another level of the canopy, by the roof of a small building under the tree or by the ground as well. Whereas some segment based methods use first and last pulse height difference to detect vegetation segments.

4.2 Discussion

Digital terrain model generation is one of the most important applications that can be obtained from ALS data. This fact can be demonstrated with the high number of developed algorithms in the last ten years. In the literature some works classify the algorithms or simply list and describe them. An elaborated description of many approaches can be found in Sithole (2005).
This new systematization of algorithms is based on the type of information applied in the filtering process. These pieces of information can be features and elements of the data processing. A filtering algorithm can use primary information, namely the laser measurements and secondary information, which are derived from the primary information. Different kind of information can be derived from the measurements, thus different information sources can be utilized in the filtering.
This new systematisation shows the speciality of our new segmentation based approach (see chapter 4.1.6).
The existing algorithms approach the filtering problem from one view, in other words they usually use only 1 or 2 sources of information. Reliability of results is higher, when this complex problem is solved by using as many different information sources as possible. Therefore, the terrain and object characteristics can be defined better.

In this section the utilizable information sources are described first. According to these sources, the existing filtering algorithms are classified in the next step and further possibilities of filtering algorithm development are recommended.

Existing filters use the following features and sources of information from laser data exclusively:

- points
- segments
- geometrical point relations
- point to surface model relation

- geometrical segment relations
- segment to surface model relation
- segment properties
- additional information

Most of the methods use *points* as an information source. Point based filters work well, when object and terrain points are equally mixed. Typical filter errors may occur, when this requirement is not fulfilled. These filter errors are caused by e.g. large industrial buildings, where points may be classified as terrain on the centre of the extended roof, or near sharp terrain edges, where terrain points may be eliminated with the consequence that the sharpness of the edge is diminished.
The strength of the point-based approach is that an explicit surface model can be used (see chapter 4.1.4). Describing the expected terrain surface with a dedicated model allows us to include terrain characterisation in the filter process. Additionally, the point-based approaches are useful in vegetated areas. It is quite obvious that in case on a flat terrain, the height jumps are caused by vegetation then checking the height differences between the neighbouring points can provide good results. The segment-based methods can provide the same results as well, if they can handle single points as individual segments.

Segment based filters perform well in urban areas. Many step edges can be found in the data and segment based methods enable us to treat whole objects in one process. The disadvantage of this approach is that no explicit surface model can be used. In forested areas it may happen that too many small segments are generated, therefore the advantage of using point groups does not appear.
Because of filter deficiencies, manual correction of filter errors is required. Point based filtering, for example, requires that areas near edges are manually checked - and if necessary edited - in order to correct filter errors. The strength of the segmentation-based approach is that during segmentation only the homogeneity within the segment is guiding the grouping process. Therefore, segments reach exactly up to the break lines and jump edges. Advantages of using segments lie therefore in retaining break lines and jump edges in urban areas. Because of this, this method is superior to filtering without grouping points into segments.

With filters using *geometrical point relations* the run of the terrain only locally can be considered. The utilized information can be the distance and the height difference of the points, the slope of the line between two points or combinations of these. These methods use these parameters as filtering criteria.

Methods using *points to surface model relations* are based on an explicit surface model, that is an approximation of the terrain surface. A rough terrain model enables us to consider not only the local but also global changes of the surface.

Segment properties can provide valuable information for the distinction of terrain and object segments. Maybe the simplest one is the analysis of segment sizes (e.g. Lee, 2004). The extent of objects is in every case limited and terrain segments may exceed the size of the largest object. Of course, in some cases terrain segments may be smaller than an object. Other segment properties can also improve the performance of the filtering, like segment shape, surface smoothness or radiometrical information.

Object and terrain segments are located in a certain order and have a regular proximity relation to each other. Statements can be done about this regularity, like 'the terrain segments are lower than the objects' or 'the objects have higher edges than the terrain'. According to these statements, the proximity of the segments can be checked and the segments can be classified as terrain or ground segments. The disadvantage of this approach is that not all proximity relations fit in this rule system, which can lead to misclassification.

In the case of *segment to surface model relation*, an explicit surface model allows us to consider the topography of the terrain not only locally, but also globally. The presented segmentation based robust interpolation method of Tóvári and Pfeifer (2005) uses explicit surface model and segments, so this is recommended as an information source.

Additional information may be used in this filtering approach like break lines, GIS (e.g. cadastre) or spectral data. These sources can provide useful information about the terrain characteristics, which can not be obtained from ALS data. Break lines strongly influence the terrain characteristics. Sharp edges can be hardly prevented from elimination in the filtering process. Therefore, the external source of these terrain structures can significantly improve the quality of the generated terrain model. Spectral information like RGB data helps to distinguish objects with similar geometry but different color.

We can see that none of these information sources provide enough information to classify terrain and object points. The frequent filter errors show the weak points of each method. These are not the same in every case, thus more information sources used in the process can improve the performance of the filter.

The filter methods can be classified on the basis of applied information. This can be seen in table 4.2. The first generation of filters, which can be seen in the first two groups, uses single points. The second generation (third and fourth groups) uses segments. Segments contain more information than single points, therefore, they are more important and highlighted in the table. The filter of Axelsson uses a mixture of surface model and geometrical point relations, therefore, it is indicated differently in the table. Filters that use surface model, work globally, the others locally. The segmentation on geometry works locally. Segment classification remains local, if it is based on the segment properties or on the proximity of the neighbouring segments. The filter of Tóvári and Pfeifer works globally and locally, since it uses surface model and segments.

	Elmqvist	Kraus & Pfeifer	Wack & Wimmer	Briese	Axelsson	v.Hansen & Vögtle	Vosselman	Brovelli	Lohmann	Nardinocci	Sithole	**Tóvári & Pfeifer**
Uses points	X	X	X	X	X	X	X					
Uses segments								**X**	**X**	**X**	**X**	**X**
Surface model (distance to)	X	X	X	X	o							X
Geometrical point relations					o	X	X					
Geometrical segment (relations								X	X	X	X	
Break lines				X								

Table 4.2: Filtering methods according to the used information sources

Of course, the results of a filter method depend on the number and type of information sources. Each information source describes a different part of the object's characteristics. The complete and exact knowledge of the characteristics of an object makes the reliable decision about its class possible. Therefore, the more information sources are used, the better filtering quality can be obtained. In an ideal case, all available sources are utilized. This shows that the next generation of filters may work on segments or objects and classify them on the basis of all their features.

Chapter 5

Segmentation

5.1 Introduction

In this chapter, some segmentation methods are described in order to show the wide palette of approaches. At the end the object segmentation method of the IPF is presented, as well as an improved algorithm (5.4).

5.2 Aim of segmentation

Segments are continuous, unbroken elements of the surface that has homogeneous geometrical, spectral properties.
The purpose of this process is to group points with similar features into segments. In the field of laser scanning, usually homogenous regions (e.g. roof facets) in respect to geometry, radiometry are segmented. Issued from the nature of ALS data, spectral information is not available, therefore e.g. the color homogeneity can not be investigated within the segments. A lot of applications need this attribute information for surface analysis or model reconstruction, therefore numerous surface segmentation methods have been developed in the last years. This process may be even more important in close-range laser scanning applications, where mostly modeling is the main goal. For this reason, a great part of these methods are designed for close range measurements. The ALS segmentations are aimed at group points belonging to the same object, object part or terrain part.
The aim of segmentation is determined by the application; homogeneity criterion of segments may vary depending on it. While e.g. smooth planar surfaces are sought for building modeling, all building points should be connected together in an object classification process, i.e. different planar surfaces (rooftiles). The desired segment properties may vary within the same application as well, depending on the object type. Therefore a global solution for all purposes is not feasible.
For example in an application, where ground point labeling and classification of vegetation and buildings is the main goal, two different tasks have to be solved at the same time. On the one hand, high frequency data should be filtered out from the terrain; on the other hand, objects should be segmented with all their details, like chimneys on roofs or vegetation

objects. Different homogeneity criteria are required here depending on the particular element of landscape. Contrary demands of segmentation would require classification of data in order to fulfil all purposes. Since in this case segmentation is a precondition of classification, this method can not be carried out. For these reasons a general solution considering all demands is not possible. At the determination of application purposes, constant homogeneity criteria should be considered. Complex tasks can be realized in more segmentation steps, when every step provides segmentation from the same data for a different part of application or in a hierarchical way, where in the first level resulted segments obtained in the higher level are resegmented in a next level, like in an image pyramid.

5.2.1 Intensity data

With respect to the nature of laser scanning, geometrical data must be used for segmentation purposes. Applying intensity data is not prosperous in consequence of their noisy character. Therefore, radiometrical properties can not control this segmentation process. (See chapter 6.4.2 about the principles of the intensity measurement). In that chapter, it is described why intensity data can not provide adequate information for the segmentation process. In fact, the geometry usually provides sufficient and adequate information for segmentation, the lack of radiometrical information does not prevent us from obtaining suitable results.

5.2.2 Over- and undersegmentation

Two kinds of errors can occur in the results of segmentation. In cases where inhomogeneous elements are connected in a segment, we speak about undersegmentation. A point of lower vegetation connected to a bare earth segment is a typical example of undersegmentation. The division of a homogeneous region into more than one segment is called oversegmentation. This kind of error occurs in cases where a homogeneous bare earth area is split up into neighbouring segments. Under- and oversegmentation errors are complementary errors in segmentation, like type I and type II errors in the field of filtering. The number of type I or type II errors does not say too much about the quality of segmentation; the sum of the errors should be considered as segmentation errors and the sum of the errors should be minimized. The importance of the different error types can be different depending on the application. For example, in the case of segment based filtering, the undersegmentation errors have much more influence on the filtering result than oversegmentation, since object points within bare earth segments must be excluded. In spite of this, in an object classification process, the chimneys should be connected to the roof segment, so the area must be undersegmented. These two examples also show that the aim of the application defines under- and oversegmentation errors, thus an exact global definition can not be given, the errors are application dependent. The evaluation of the segmentation results can be carried out only in respect of the particular application. In figure 5.1, the two segmentation error possibilities are presented. On the left side, the roof of the house is divided into several parts, while on the right side, the segment borders do not fit with the border of the roof tiles.

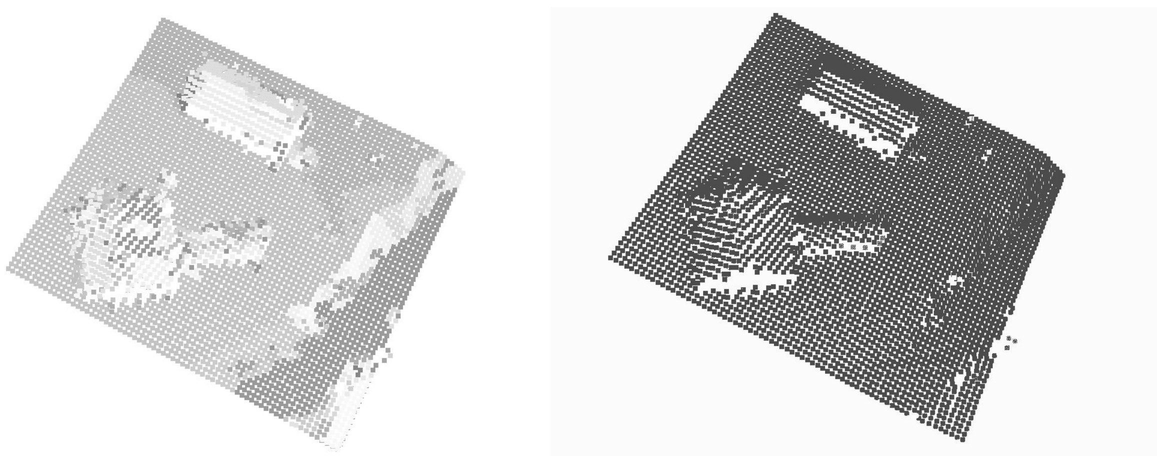


Figure 5.1: Oversegmentation and undersegmentation

5.2.3 Effects of point density and distribution

The results of the segmentation procedures are not independent from the point cloud density. At low density, the run of the implemented surface is smoother. The lack of spatial information (e.g. edges that loose their sharpness) makes it difficult to find the segment borders. In case of high point density, the run of the surface is more complex. More details of the topography are presented, which might be unimportant considering the task. The segmentation methods may produce too many small facets and the area may be oversegmented.

Anisotropic point distribution can be observed in cases where the point density is not the same in every directions. It means, the run of the surface is measured in more detail in one direction, therefore the obtainable detailedness is not homogeneous. There is no perfect method to solve this problem. Data can be rasterized or triangulated, but the former suffers from a loss of information and also the latter does not provide a real solution.

The anisotropy of point distribution confuses these problems and while in one direction too raw surfaces are generated, in the directions of anisotropy small details split up the area. Some segmentation methods meet problems due to the so distributed data, since the selection of n nearest neighbours is affected by the anisotropic data. In case the point density is 10 times higher in a direction than to the perpendicular direction, then the 10 nearest neighbours can be located on a line, which can make the adjusting plane estimation ambiguous.

As it has been mentioned before, some of the segmentation methods are developed for terrestrial laser scanner data, which has a bit of a different data characteristic. While in ALS data the segments are located vertically mostly in one or two levels, in TLS data the surfaces may be positioned at any levels and in every direction.

5.3 Segmentation methods

In the following part, some of the possible segmentation methods will be shortly presented and discussed. These approaches aim to generate homogeneous regions. They segment usually last pulse data, the few exceptions will be mentioned.

5.3.1 Region growing based segmentation

This type of segmentation method is based on region growing. These approaches group points based on geometrical relations of neighbourhood like height difference; slope difference; difference of normals; or curvature difference. The method of **Lee and Schenk**, 2001, works on triangulated data and is driven by a robust plane fitting. **Roggero** (2002) presented an approach that combines a hierarchical region growing with principal component analysis (PCA) on the generated n-dimensional feature space. Two algorithms are proposed: the first is based on geometrical descriptor mapping, where one or more properties like static moment, curvature or junction are computed and mapped for each point and then region growing is performed with reference to the property map. The reflectance of measurements is also considered in the feature space. The second algorithm does not perform descriptor mapping to realize a faster method.

A method based on clustering analysis is proposed by **Filin** (2002). It uses the position, the best fitting plane parameters, and height difference of neighbouring points. Other variants of cluster analysis can be found in **Hofmann** (2004) and in **Alharthy and Bethel** (2004).
Vosselman and Dijkman (2001) propose Hough-transformation to detect planar roof surfaces within given building boundaries.
In **Hoover et al.** (1996) a two step region growing method is presented. Firstly, normal vectors of, and residuals to a trend surface are calculated for each pixel in a window. The pixel with the smallest residual is taken as the seed point. The region growing process takes into consideration the difference of normals, the distances of points and the distance between the new pixel and the plane of the region growing. Segments which are too small are excluded.
The procedure of **Flynn and Jain** (1991), and **Hoffman and Jain** (1987) connects pixels

in a range image based on clustering. First, an edge detection process based on height differences of neighbours is performed. Normal vectors are calculated for pixels that are far enough from the edges. Clustering on these vectors provides a connected set of similar surface normals. Pixels belonging to the same cluster are labeled identically. In order to avoid undersegmentation, the area must be oversegmented and in a final step, neighbouring segments can be merged, checking the similarity of normal vectors and heights, in order to join similar neighbouring segments.
Lohmann and Jacobsen (Jacobsen & Lohmann, Lohmann, 2003), **Schiewe** (2001) and **Hofmann** (Hofmann et al., 2002) segment rasterized laser data with the **eCognition** software (Definiens Imaging GmbH), which works also on the region growing principle. Rasterized height data are considered and processed as an image. It uses a "bottom up region-merging technique". It starts with single pixel objects and in numerous steps these small objects are merged into bigger ones. The average image object heterogeneity is minimized over the whole area. Heterogeneity is based on the standard deviation of the grey values of the objects and on their shape as well. Multiple datasets can be used in this segmentation process, in order to get reliable results. Lohmann and Jacobsen (2003) apply intensity data besides height image while in Hofmann a slope and a laplacian filter image of the laser data are added. Lohmann and Jacobsen state that although the additional information does not improve the accuracy, the reliability of the produced class grows.

Edge based segmentation is a special case of region growing algorithms, since the points are not connected based on geometrical relations, but within a closed boundary of an object.
It is assumed that objects are limited by closed edges. This assumption is usually appropriate, but the method fails, when transition between neighbouring objects is smooth. These methods work on rasterized data, therefore, image processing tools can be applied. Firstly, an edge detection filter is used to provide a base for the region growing method. The segment grows between the boundaries, the edge determines the segment extension. In the case where the edges are not closed, the growing region runs out from the object boundaries. Morphological tools can help to some degree in this problem.

Terrain surface segmentation

The segmentation method of **Pfeifer** (2004) is used in the segmentation based robust interpolation (Tóvári & Pfeifer, 2005) for terrain extraction, which is described in chapter 4.1.6 and the experiments are presented in chapter 7, thus it is described in detail. The aim of this segmentation is to form homogeneous terrain segments, without mixing object points into them. This approach is able to segment smooth surfaces that are approximately plane. A plane model is suitable to describe the local terrain surface, but it can not represent the terrain characteristic in a hilly site.
The segmentation method applied here was originally developed for terrestrial laser scanner

data. It is based on a region growing process and uses the n nearest neighbours of the points. These neighbours are used in the first preprocessing step to estimate the normal vector for each point. The region growing algorithm first picks randomly a seed point and then examines the n nearest neighbouring points whether they fulfill certain criteria or not. An adjusting plane is estimated for the points of a segment. This plane is an orthogonal distance regression plane, since errors in all three coordinates are assumed. Points from the n nearest neighbours will be connected to the segment, if they fulfill three criteria:

- similarity criterion of the current and candidate points normal vectors (α),
- distance criterion of the candidate point to the adjusting plane *(r)*, and
- distance criterion between the current point and the candidate point *(d)*.

The first one (similarity of the normal vectors) means that the angle difference between the current and candidate points' normal vector should be under a predefined threshold, using the normal vectors from the preprocessing step. This criterion excludes the large changes and enables only the smooth transitions between points. The adjusting plane is recalculated after each accepted point, and its distance to the new candidate must be shorter than a predefined maximum value. Points closer than the threshold to the adjusting plane are considered as points on the same surface. The maximum distance of the current and the candidate points must be also below a certain value. Very far points with a similar normal vector may lie on another surface, therefore, they should not be joined to the growing region. Growing continues until no more points can be found fulfilling the criteria. The method starts again finding a new seed point.

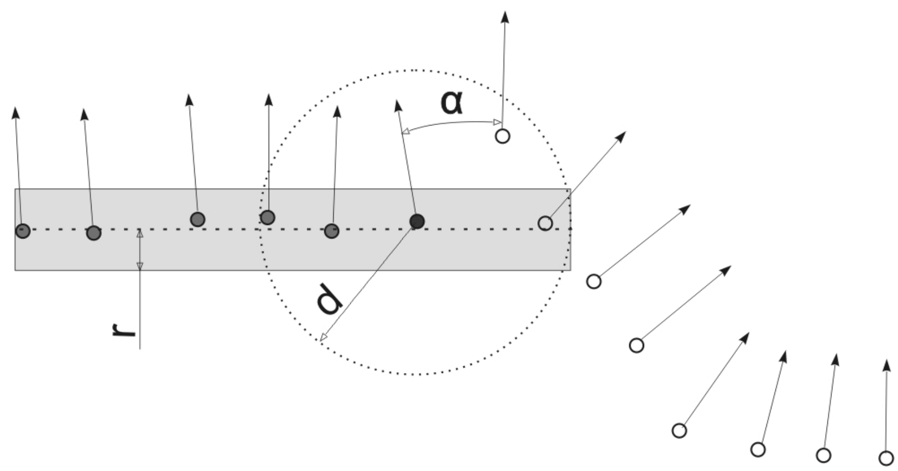


Figure 5.2: Parameters of the segmentation (gray points- accepted points, black point- actual point, white points- not (yet) accepted, dashed line- adjusting plane, arrows- normal vectors). The gray area represents the distance criterion of the point and the adjusting plane.

The process is affected by 4 parameters: n, α, r, and d. The parameterisation is influenced by the characteristic of the data set. The density of the data can be accommodated by setting the number of neighbours and the maximum distance for accepting points. Points that are not part of any surfaces are individual segments. The practice shows that these are points of vegetation, vehicles, chimneys, power lines or other outliers, but they may occur as ground points in densely forested areas as well.

The eigenvector/eigenvalue approach using the 2nd moments of the point coordinates are used for the plane adjustment. As the plane is not parameterized over the xy-plane, also vertical walls can be extracted. Likewise, stacked horizontal surfaces may form two segments where one is above the other. The matrix of moments can easily be updated after adding one point. In this way the 3D content of the data is taken into consideration, which is the correct procedure -considering the ALS data characteristic. This method is suitable to separate smooth surfaces, therefore, it is used for terrain extraction in the segment based robust interpolation method.

The type of neighbourhood can seriously influence the results of segmentation. An unsufficient solution may loose information that exists in the data or makes data reconstruction complicated.

5.3.2 Graph based segmentation

These methods presume that points within the segments are closer to each other than to points in other segments. Firstly, a proximity graph is built on the point cloud. Each edge gets a value according to the predefined proximity measure (Zahn, 1971). This can be e.g. a minimum spanning tree graph or a Delaunay triangulation.
According to a predefined criterion, edges, which do not fulfill this requirement will be removed. Segments are defined as the connected elements.

5.3.3 Segmentation by profile intersection

This approach is described by **Sithole** (2005). The method offers a fast and relative simple solution for the proximity analysis problem of the neighbouring segments. The approach construct surface-wise segments from pieces of lines. These lines are combined together if they are on the same segment.
Three directions are indicated on the data set and the whole area is divided into equally wide profiles in all these directions. Points are connected into line segments in every profile when they are on the same surface. This connection of line segments can be realized by diverse methods like curve fitting, consecutive labeling, proximity labeling or minimum spanning tree labeling. This procedure results in line-wise segments in every profile.
Line segments from the differently directed profiles are combined so that line segments

passing through the same point belong to the same surface-wise segment. Every point is segmented 3 times according to the 3 profile directions. Lines passing through the same point are combined together, so they constitute surfaces. The segmentation depends on the thickness of profiles, the number of directions (3 in most cases) and the line segmentation method. The last one has the greatest impact on the final result.
The approach is able to segment overlapping surfaces like bridges and profiling enables fast processing, but anisotropic distributed data may cause problems for profile segmentation.

5.3.4 Neural network based segmentation

Neural networks often process remotely sensed images and range images used for image processing tasks like image segmentation or pattern recognition. However, this restricts the application basis onto rastered data, networks can be designed for point clouds as well. Neural networks have the ability to extract meaning from complicated and imprecise data, and can solve problems that has too complicated algorithmic solutions.
The Kohonen type Self-Organizing Maps (SOM) [Kohonen, 1995] based on the unsupervised learning of the neurons, are able to consider the topography of networks, however the construction can be organized only in fixed regular networks (square, triangle, hexagon). The network dimensions are equal to the dimensions of the analyzed raster size and every oscillator represents a single pixel. Oscillators are connected to their 8 neighbours, but the extent of neighbourhood can be increased at the expense of computing time.
In the 'locally excitatory globally inhibitory oscillator network' (LEGION) (Wang et. al 1995), oscillators have excitatory lateral connections to the neighbouring oscillators and also to a global inhibitor. The approach works similarly to the *cellular neural networks (CNN)* [Wang, 2004]. In figure 5.3 a small example can be seen, segmented by the algorithm of Wang. Last pulse data is processed, therefore, only buildings and the vegetation partially can be seen. Pixels of a segment are indicated by the same shade of grey. In this example, only the heights of the points are considered, therefore steep surfaces (e.g. steep roofs) are oversegmented.

Neural gases offer a solution that is free of the restrictions of a fixed network, therefore it can represent the measurements distribution better than the fixed structure of a neural net. The structure organizes itself during processing, so the topography changes constantly, moreover the number of neurons is also not fixed. Since this method has not been used with ALS data, the efficiency could not have been evaluated yet, however, the idea is promising.

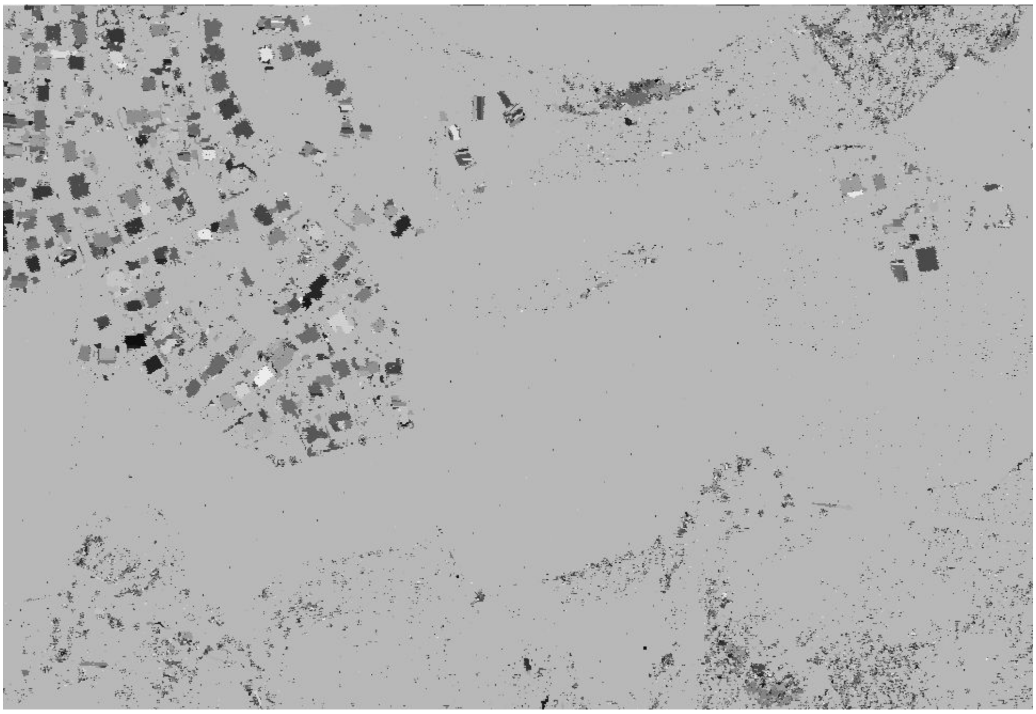


Figure 5.3: Segmentation by LEGION method

5.4 Object segmentation

In the following, segmentation methods are described that are improved and developed respectively in this work. The experimental results are discussed in chapter 7.2. As it is mentioned before, segmentation aims are different in case of terrain detection and object classification. Therefore, these processes are divided into two parts. First, terrain points are detected on the bases of segments that are suitable for terrain modeling. In the next step, the remaining objects are segmented and classified as buildings or vegetation. In the following section, the object segmentation approach is presented and discussed. Object segmentation aims to build segments only from the objects over the terrain surface, like buildings or trees. In a subesquent classification process, these segments will be classified (see chapter 6.3).

5.4.1 Region growing based object segmentation

This method is first described in **Vögtle et al.** (2000) and works on the region-growing principle. As it is developed first for building detection and segmentation, it is not sufficient for detection of small objects and vegetation, but performs very well in segmentation of buildings, where also the most outliers, such as chimneys or antennas are connected to the building segment.
Since the method investigates the height difference of the neighbouring pixels and the absolute height above ground of the candidate pixel, the influence of topography should

be excluded. Therefore in the first step of this approach a so-called normalized digital surface model (nDSM) is created (e.g. Schiewe 2001). For this purpose a rough filtering of the original laserscanning data (DSM) is performed to extract points exclusively on the ground (DTM) even if some ground points at sharp terrain edges are excluded. This filtering is based on the convex concave hull approach (von Hansen, Voegtle 1999) which results - by an accordant choice of the filter parameters - in a rough trend surface of the terrain (rough DTM) through the lowest points without vegetation or building points. Now the resulting nDSM is calculated by subtracting this DTM from the DSM. In this data set all 3D objects on the surface of the terrain remain, in some cases also a few terrain objects are included caused by rough rocks or sharp terrain edges, where the trend surface was not able to follow these complex topography. It is evident that this result is not perfect because of non-relevant objects - in this case, because of the terrain and small objects. These can be excluded after the subsequent segmentation and classification process.

Favourably, the segmentation of relevant 3D objects is carried out in such a normalized surface model (nDSM) by in a special region growing algorithm, which extracts and separates 3D object areas. The starting point (crystallization point) is a pre-defined neighbourhood of a point (e.g. N8) in this data set where all points exceed the minimal object height above ground (e.g. 2.0m). During an iterative process all new neighbouring points are joined into this segment, which satisfy the maximum acceptable height difference homogeneity criterion. The theory of this pre-condition is that the slope of a man made object surface (e.g. walls) has a maximum possible inclination angle. However, this is not true in some cases. It may happen that it joins together e.g. roof points and low chimneys while it may separate this roof part from an other roof, which is located on a different height level. Of course, it can not be guaranteed that neighbouring pixels will be joined together if they have a height difference higher than the maximum acceptable one (homogeneity criterion). Not only the height differences are considered in the region growing method, but also the absolute heights of the points in the nDOM, i.e. the heights above ground. In case the point is under a predefined height, it will not be connected to the segment. This threshold represents the minimum height of an object that can be detected. This procedure results separated 3D objects like buildings and dense vegetation, while very small and low objects are excluded. Figures 5.4 shows the segmented objects of a test site. Some experiences are described in chapter 7.

This method has been improved to differentiate better the building and vegetation objects. It is described in the following part.

5.4.2 Object segmentation by first and last pulse differences

Since the approach is based on height and proximity and does not utilize the local normals, it usually results in a slight undersegmentation, depending on the parameterization. Neigh-

Figure 5.4: Segmented objects of a test site

bouring objects standing close to each other - with a smooth height transition between them - may be connected in one segment, whether their common border represents a sharp edge or height step or not. This may happen when e.g. a tree crown grows over a housetop or when a gabled roof building stands on a steep slope. Undersegmented elements that contain points from diverse object types may confuse the classification process and result in classification errors. A segment should contain points only from one object class, therefore such kind of undersegmentation must be avoided. Two opportunities will be shortly described to divide these segments:

1. subsegmentation of the detected 3D-objects
2. segmentation by a modified process considering other geometrical features as well

Theoretically, both solutions can produce the same results, but technically, the second one is more complicated and requires more effort.
Members of two classes (buildings, vegetation) may be mixed in the object segmentation process. These two classes have individual characteristics, therefore, it is possible to separate them in the segmentation. The crucial feature is the height difference of the first and last pulse. The extension of a tree crown makes it possible to penetrate it by the laser beam at multiple positions. Trees can be seen in the height differential images and can be distinguished easily from the other type of objects. Trees have 2 dimensional extension on the ground plan. The points of plants form bushes, the isolated points visualize other type of objects. Building boundaries appear as lines (see figure 6.2 in chapter 6.4.1). The analysis of this feature in the segmentation process may help to separate buildings and vegetation. The connected areas at the border of the segments probably constitute vegetation, while tree crowns may grow over the roof. Therefore, the algorithm has to

prove if the sub-segment takes place at the border of the segment. This would be very complicated to perform during the segmentation, so the first solution, the resegmentation has been developed.
A region growing method is used to segment areas with high first and last pulse difference. High differences between the echoes can occur not only at building borders but on the housetops as well (e.g. by antennas, chimneys, or power lines over a house), therefore only pixel groups at the segment borders are considered. Each pixel of these groups must satisfy the condition of the minimum echo difference. Vegetation is assumed where all height differences are above a threshold. The seed point is selected at the boundary of the segment which is of interest, in case the first and last pulse difference is above this threshold as well. Transmission lines over the top of buildings can be suitable for this condition and could divide the segments. Therefore, line objects are also excluded, they are not considered as vegetation. These line objects can be tested simply by counting the neighbouring pixels corresponding to the echo difference criterion. For example, every pixel of a power line has less than 5 neighbouring pixels that are able to fulfil the echo difference criterion. The local compactness of the pixel groups are investigated. Pixels, which have less than three neighbours satisfying the echo difference condition, are lines. In this way, it will be possible to reject power lines as vegetation. A comparison of the original and the improved method can be seen in figure 5.5. On the left side the segments (black) and the significant first and last pulse differences (green) can be seen. On the right side the new segments (black) and the removed segment parts (gray) are presented.

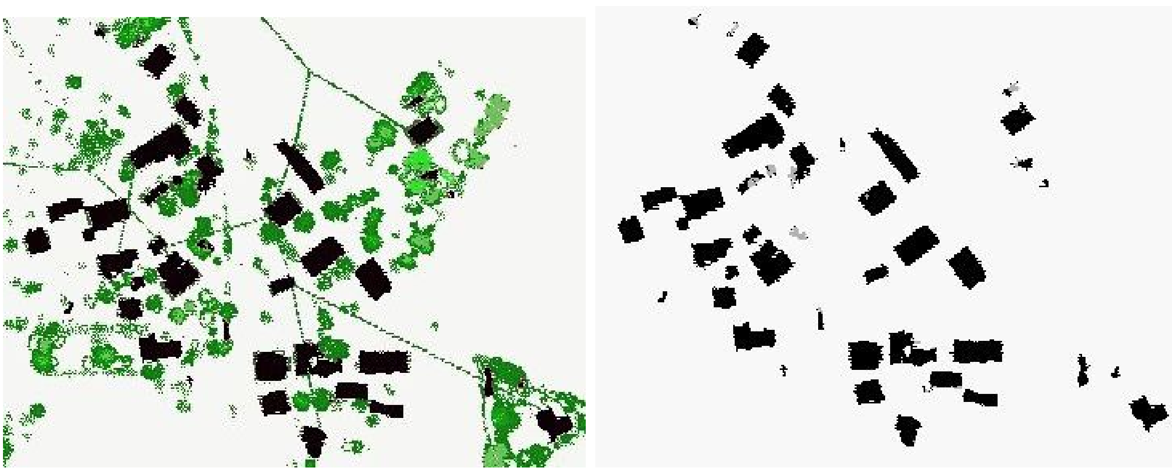


Figure 5.5: The effect of considering the first and last pulse differences. On the left, vegetation (green), power lines and buildings are presented. On the right, segmented buildings by first and last pulse differences (black) and original segments (grey) can be seen. Vegetation over the roof causes segmentation errors.

Tree canopy parts over house roofs may cause the cutting of the building segment. This unfavorable effect can be seen on figure 5.6. White indicates the building segments, while black shows the removed building parts, caused by the high first and last pulse difference above it.

Figure 5.6: The effect of a tree crown over a building. (White - new segments, black - removed segment parts).

5.5 Discussion

In this chapter some segmentation methods are presented, which are developed for applying them in the field of digital image analysis, remote sensing or laser scanning. These approaches are based on certain assumptions. These semantic assumptions are translated to conditions in the algorithms that control the segmentation procedures. All of them are quite simple assumptions for making a realizable algorithm. Assumptions can be e.g.

- a point within a segment is closer to another point in the same segment than to a point in another segment
- points within a threshold of an adjusting plane or other mathematically easily describable surface belong to a segment
- height difference, normal vector direction difference, local curvature difference or other local features between neighbouring points in a segment are within certain thresholds.

Since these methods are not based on complex assumptions, they are specialized on segmenting a certain kind of surface or object. The object segmentation process is also based on some geometrical conditions of the heights of rasters and neighbouring rasters. Smooth transition between neighbouring objects causes these objects not to be separated from each other. This drawback is disadvantageous, especially if different type of objects are undersegmented. To solve this problem, an approach has been developed in order to divide segments. This method detaches segments on the basis of first and last pulse differences. It is suitable to remove vegetation parts from the segments. The basic assumption is quite simple, therefore, the algorithm is limited in terms of reliability.
General algorithms that can segment different kinds of objects with acceptable results do not exist. In cases, where more types of objects should be segmented (e.g. artificial and natural 3D objects, terrain points), more particular methods should be applied. An approach for terrain point segmentation that could take the characteristic (e.g. the local curvature) of the terrain into consideration, does not exist either.

Chapter 6

Classification

6.1 Introduction

A class is a set of natural or artificial elements, which have similar or the same determining properties. The elements of a class must be defined clearly, otherwise ambiguous classification can happen. On one hand, defined classes should cover all the elements, otherwise some elements remain unclassified. On the other hand, an element should be sorted solely into one class, in order not to sort a kind of element into different classes.
Elements of the physical world belong to the same class, when they have similar geometrical, spectral etc. properties. An element of the physical world belongs to that class, where the class elements have the most similar properties.
The aim of classification in this work is to label laser points that belong to the same type of object.
The classes may also depend on the application, e.g. bridges can belong to the terrain class or to the object class as well. A typical process is called filtering, in which points are classified as ground or off-terrain points. Since the data acquisition provides discrete measurements, point distribution and density also have influence on the definable classes. On one hand, dense measurements might emphasize unimportant small details, on the other hand, in a point set, where measurements are far from each other, important features and elements might be lost.
A discrete point of an object does not carry all those features of the object, which provide basis for classification. A point of a building roof can represent the height of the object, but not its extension or shape. Classification of single points is a reduction of adaptable features, therewith a limitation of possibilities. Therefore, it is more advantageous to define object types and classify objects as an 'object oriented method'.
Objects on the surface of the earth usually have special characteristics, which enable their classification into certain classes. When a value of an object attribute is given, some conclusions can be made about the probable class of the object. If more possible classes can be determined, then the membership is uncertain. A 25 m high object in a rural area is most probably a tree, but it should not be excluded that it is a building. In an urban area, the uncertainty is too high to decide about the class in this case. For

this reason, namely, through the overlap between the classes, usually one attribute is not enough for making decisions. In most cases, objects can be classified into one certain class if appropriate attributes are investigated. When object height or shape does not provide enough information for an unambiguous classification, maybe color or material makes it possible. ALS is limited in respect of the kind of acquired information, however in most cases is still provides in most cases enough geometrical attributes of an object to give a decision in the classification process.
Exact definition of a class improves the quality of classification. The more features used for the class definition, the more accurate description can be given. For example, the class of 'buildings' can be described more accurately if not only their 'shape', but also their 'extent' is investigated. Since objects have more features than points, object classification can be performed on a higher quality level.
Selected features should be representative and not correlated. Correlated features, e.g. different kinds of height textures do not support the classification, because the correlated property plays a major role, so classification loses its balance.
Usually classification based on one feature is not reliable, since the intersection of different sets -corresponding the classes- are not empty sets.

6.2 Previous work on ALS data classification

6.2.1 Point based classification in ALS

The point based classification process is based on the analysis of the geometrical features of one single laser point. Taking a discrete point of the surface and comparing its properties to another point, the obtainable information is restricted in terms of the nature of the sampled surface. The limited number of point features allows only simple classifications. Terrain point labeling for DTM extraction is maybe the most investigated procedure in ALS data processing, where points are labeled either as ground points or off terrain points. Most of the filter algorithms belong to the point based classifications, although the latest research aims to perform filtering on segmented data or on classified data using different parameters on the different classes. Point based filtering methods are presented in chapter 4.1.

The point based method of Elmquist (2001) classifies pixels that are at least 2m above the ground as vegetation or buildings. This method is based on the height texture to distinguish artificial and natural objects. The height texture in this case is the maximum local slope and the second derivate of the pixel and the 8 neighbouring pixels. In addition, the number of double echoes is also used, while it is less within the building boundaries as within the vegetation. The objects are filtered with a median filter before the classification, in order to reduce the noise, caused by small objects like chimneys.

6.2.2 Segment based classification

A special case of segment based classification is the segment based filtering, where the segments are classified as ground segments or non-ground segments.
The segment-based filters are typically designed for urban areas where many step edges can be found in the data.
The segment classification can work well, when every segment is equal to one object. This task meets ambiguous requirements (see chapter 5.2), therefore proper results can not be performed in one segmentation and classification process. Consequently, we do not aspire to solve the whole classification problem in a single segmentation and classification process. One process aims to detect the ground points, namely filtering the dataset, and an other process aspires to classify the objects on the ground. It is suitable to perform the filtering first and then the object segments can be classified. This workflow can be considered as a multi step algorithm.

In the segment based algorithm of Sithole (2004) a 4 step procedure is proposed to classify the data. It detects 'macro objects', bridges, 'micro objects' and the man made and natural objects. The segments are classified depending on their geometrical relation.

A special segment based classification application can be seen in Barsi et. al (2003), where vehicles on the highway are classified in ALS data by a clustering method.

eCognition

The eCognition (from Definiens) software works on a segment-based classification method too. It is widely applied for image classification, so it can not process point clouds, only gridded laser data, it belongs to the 2.5D methods. Connecting all segments, the content of the data is represented as a network of segments.
According to Definiens (Definiens, 2005), the knowledge base is created by means of inheritance mechanisms, concepts and methods of fuzzy logic, and semantic modelling.
The segment classification extracts various features of the segments and the membership of the segments are decided upon after the analysis of these features.
The segments are connected as a network in one resolution level and among other resolution levels. This hierarchical approach allows us to consider the neighbouring relations of segments in one level and dependencies among levels. eCognition can perform sample-based and knowledge-based classification or a combination of these. Sample-based classification works on a fuzzy approach of nearest neighbour clustering. This approach detects similar segments in the multidimensional feature space, based on training samples.
Knowledge-based classification operates on fuzzy rule-based method. Fuzzy sets of selected object features are defined by membership functions. These functions can be determined a-priori by the user's expert knowledge. The fuzzy sets can be combined with the *and*, *or*

and *not* logic operators.

Segmentation and classification works iteratively to optimize results. Class membership of the segments is taken into consideration in the next step of iteration. It makes possible to aggregate segments into a new segment or to divide large segments.

eCognition suffers the disadvantages of raster based methods. In Lohmann and Jacobsen (2003) not only last pulse height, but intensity data is also utilized. Their investigation shows that intensity data does not improve the quality of classification, because of its noisy character. Additional first pulse data would also not be meaningful, since it contains information about another layer, so it can not refine the segmentation, classification results. Therefore the number of applicable features is limited, less classes can be defined than in multispectral image classification.

6.3 Object classification

This procedure is in fact a segment classification method. The 'object' term is used here instead of 'segment', since the applied segmentation method provides segments, which are large objects like buildings and trees. Since these segments are objects, therefore, the approach is called object classification.
This approach is a part of our terrain and object classification process. After the object segmentation, classification is required upon the extracted segment features. The experiments with this method can be seen in chapter 7.2.
This idea was described first in **Schiewe** (1999) and was designed for a semi automated surface extraction. In **Vögtle** and **Steinle** (2003) an object segmentation and classification method is proposed for building and vegetation detection. It classifies the previously segmented data with fuzzy logic or maximum likelihood method upon the extracted features of the segments (Tóvári and Vögtle, 2004). The available features are described in section 6.4. In these works, segmentation is based on the normalized DSM of the last pulse data (see 2.4.2). the object segmentation method is described in chapter 5.4. In this work, these segments are classified into 3 classes: building; vegetation; and terrain segments. The quality of the result does not depend directly on the accuracy of the generated nDSM. In case larger terrain parts remain in the nDSM, they can be segmented, classified as terrain and put back into a new terrain model generating process. Since only larger objects can be segmented, only these elements will be classified. It is not appropriate to label terrain points, since small objects and off terrain points are not segmented, therefore these points can not be separated. Buildings, vegetation and larger ground objects can be classified.
The basic concept of segment classification works with different segmentation methods as well. In our experiments fuzzy logic method and maximum-likelihood method are applied. They are presented in chapter 6.5 and 6.6.

In case all the points are segmented, the classification process is able to label ground points as well. A similar concept is used in the eCognition software as well.
The object segmentation, feature extraction and classification methods are implemented on raster data structure, but it would be possible to realize the whole process on a TIN basis. This has not been done in due to the lack of time.
The classified building and vegetation objects can be removed from the dataset and a second filtering process may filter out the smaller outliers. The procedure should be parameterized in a way that the bigger objects are already removed from the dataset. This step would have an effect, like a hierarchical approach can provide.

Parameterization

Parameterization is the process in which the classifier is taught the classification rules and the characteristic of each single class. This process can not be completely automated, the inspection of a human operator is always necessary, therefore, it is the most time consuming part of the classification. Properties of elements belonging to a class must be determined accurately and the corresponding parameters must be determined according to this. The classification errors can be minimised only by a suitable parameter set. This is very difficult to determine, since the significant spectrum of the occurring object features in every class should be known.

6.4 Features

As mentioned in chapter 6.3, the classification of segments is based on their properties. These properties may be

- geometrical features,
- radiometrical features,
- topological features,
- segment to surface model relation.

Geometrical features are the properties derived from point location and the geometrical properties of a segment, like size or shape. Radiometrical features are determined by the reflectance of measurement (intensity) or - if available - by additional spectral information. Topological features compare spatial positions and relations resp. of neighbouring segments. The segment to surface model relation allows us to include terrain characterization in the classification using the description of the expected terrain surface.

6.4.1 Geometrical features

First and last pulse difference

Most of the airborne laser scanner systems are capable of recording more than one echo. Usually the first and last echoes are detected and stored (see chapter 2.1), but some systems can record up to five echoes apart with the use of full waveform analysing instruments. While the first echo is reflected back by the upper object part in the way of the laser pulse, the rest of the pulse can continue its way and hit a further object or object parts. The ALS service providers deliver the data in one dataset or first and last pulse data separated. In the first case, it is possible to calculate the height difference of the first and last echo of the same pulse. When first and last echoes are recorded to different datasets, the coherent data of a pulse in these datasets are usually impossible to find. Therefore, the differences can be calculated only locally, e.g. within a raster as the highest first pulse and the lowest last pulse measurement. So it can not be guaranteed that this value represents the height difference between the echoes of the same pulse.
Since the laser ranger can only detect an echo if the signal strength of the previously detected one is already below the detectable limit, the smallest measurable range depends on the pulse width. This can be calculated by:

$$R_{dmin} = \frac{1}{2} \cdot c \cdot t_{pulsewidth} \tag{6.1}$$

For example R_{dmin} is 75cm for the TopoSys Falcon II system, which has a 5ns pulse width. It follows that the range difference below this threshold is not caused by the first and last pulse observation of a single measurement. These small differences are caused by the

rasterisation method of the data. This is the reason, why height difference values on the vegetated areas may be smaller than the measurable (compare 6.1 left and right side). According to these data storage differences, these datasets are also slightly different (see fig. 6.2 and 6.3).
A third possibility to compute height differences of echoes can be implemented when the first and last pulse data are recorded in different datasets and the purpose is to stay in the vector domain. In this case the proper solution is to generate TIN models both from first pulse and last pulse data. Vertical differences can be computed between the models by interpolation in any arbitrary point or at the locations of first or last pulse laser points.

The differences of first and last pulse measurements show the locations, where a pulse is partially reflected back from one elevation. Building roofs normally consist of solid material, so - depending on the slope of the roof plane - no or only smaller differences between first and last pulse measurements can be observed. At building borders and vertical walls, high values appear according to the object height. In contrast to roofs, larger differences will occur at vegetation objects, since its canopy is partly penetrable for laser beams. Power lines can also partially backscatter the laser pulse, therefore they can be observed in this dataset as well.

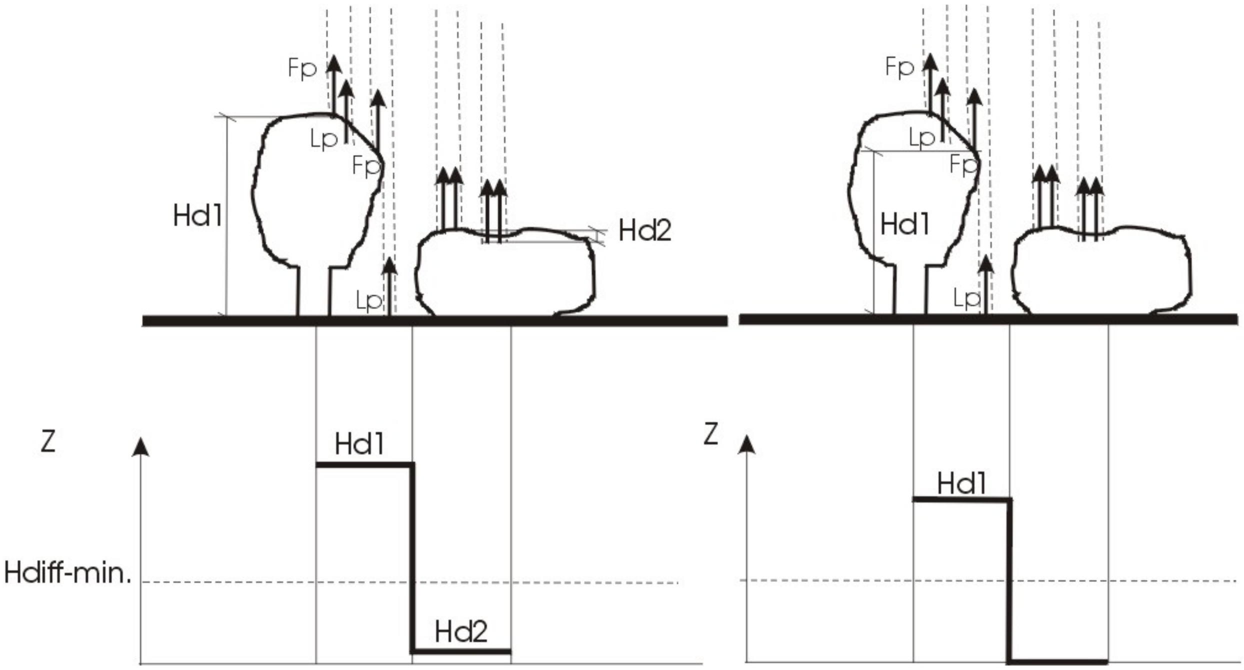


Figure 6.1: Calculation methods of first and last pulse differences. 2-2 raster elements are presented in each figure. On the bottom, the calculated values can be seen. On the left side, differences are calculated within a raster, therefore the rasterisation has an effect on the values. On the right, values represent the real differences between the corresponding first and last pulses.

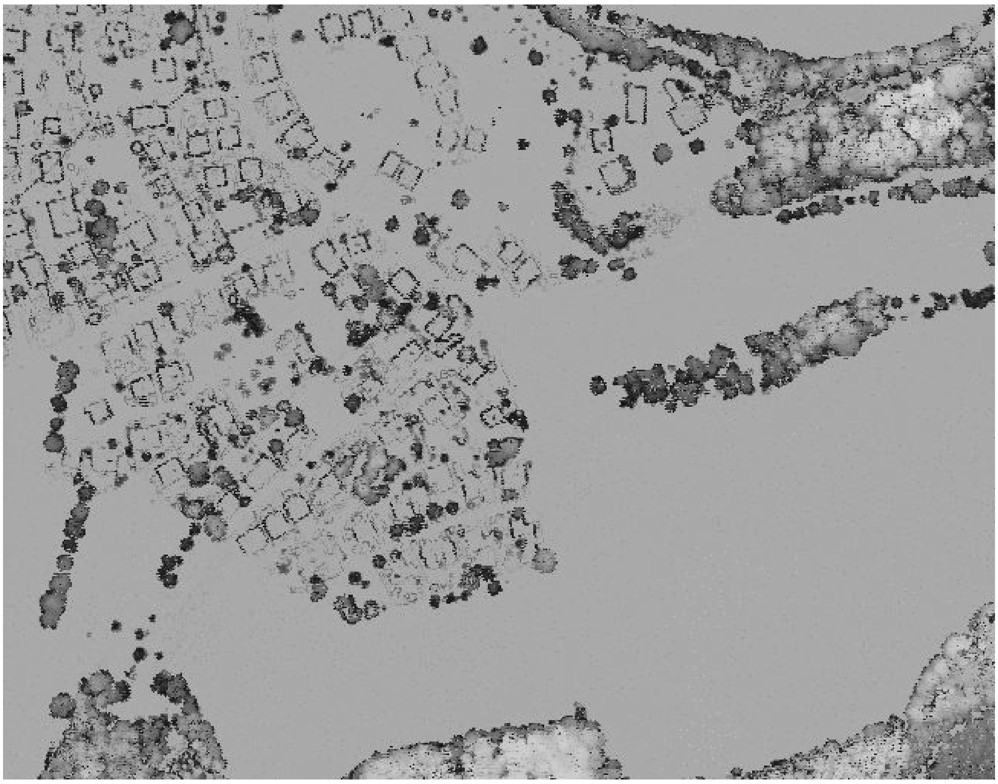


Figure 6.2: First and last pulse differences

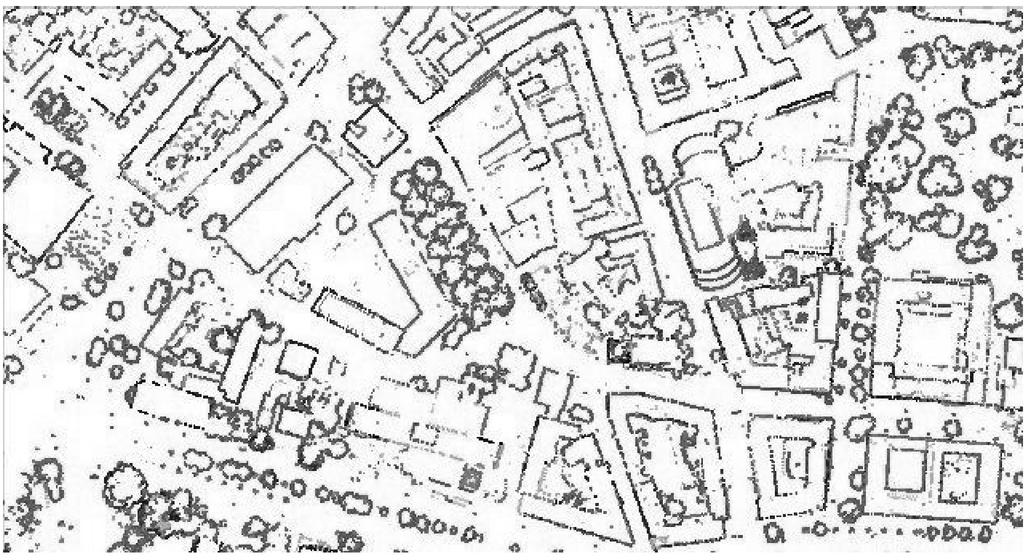


Figure 6.3: Differences between first and last echo (Schnadt, 2004). Data acquisition was carried out in summer and first and last pulse differences are calculated by every single measurement. Consequently these differences at the border of trees are significantly higher than inside.

Height texture

Height texture is the variation of height values in respect to the neighbouring pixels (Steinle, 2005). Height texture and first/last pulse differences allow the distinction of vegetation and buildings. Taking the shape of building roofs into account: exclusively those height texture parameters seem to be useful that model the deviations from oblique planes which fit very well to the characteristics of buildings in laser scanning data. Suitable results can be obtained by the Laplace operator (Maas, 1999) or by local curvature (Steinle, Voegtle, 2001), i.e. the difference of subsequent gradients in the four directions across a raster point. Inside the roof planes of buildings, small height texture values will be obtained while vegetation objects cause significantly higher values.

Standard deviation of the heights Standard deviation of the point heights can be used as height texture. In cases, where many laser points are within a raster, it is worth computing the raster value from these measurements. Since in this case the feature is computed from points located in a certainly smaller area, these results are more "centralized", i.e. less affected by points further away from the pixel center, as features that are computed by a moving weight matrix (e.g. by a $3 \cdot 3$ matrix).
Three kinds of calculating solution can be done (figure 6.4). First is a 3 D solution, where standard deviation is computed over a tilted plane. A 2.5 D solution can be implemented over a tilted plane, where a parameterization of a surface is a function of x and y. The third method calculates standard deviation over a horizontal plane.

Laplace operator and local curvature Local curvature is similar to the widely used Laplace operator, which can be described with the following formula:

$$\Delta f(x_0, ..., x_i) = div(gradf(x_0, ..., x_i)) = \Sigma_i \frac{\partial^2 f(x_0, ..., x_i)}{\partial x_i} \tag{6.2}$$

where f = an arbitrary function.

The discrete version of the operator uses a weight matrix to compute the value of central pixel taking into account the weighted neighbouring pixel values. The weights depend on the distance between the central pixel and the calculated pixel, and the sum of weights is zero.
A special case of Laplace-operator (Maas, 1999) is the local curvature operator. Here, the difference of subsequent gradients is calculated in the four directions across a raster point considering their height value and distance from the central pixel. The result is the gradient difference of the two neighbouring pixels in one direction. The local curvature is the maximum value of these gradient differences, which are computed in four main

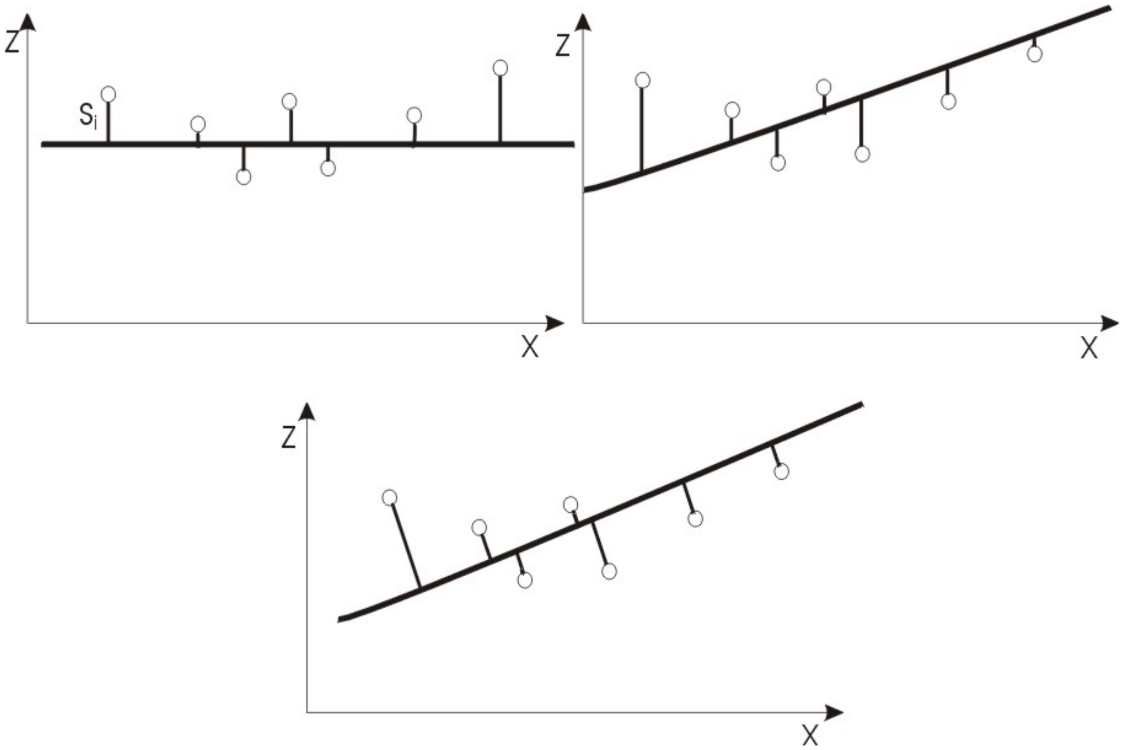


Figure 6.4: Computation of root mean square errors. Measurements are represented by circles, the trend surface and residuals are represented by lines. Standard deviation over a horizontal plane is shown on the left, 2.5 D solution over a tilted plane on the right, and 3 D solution at the bottom.

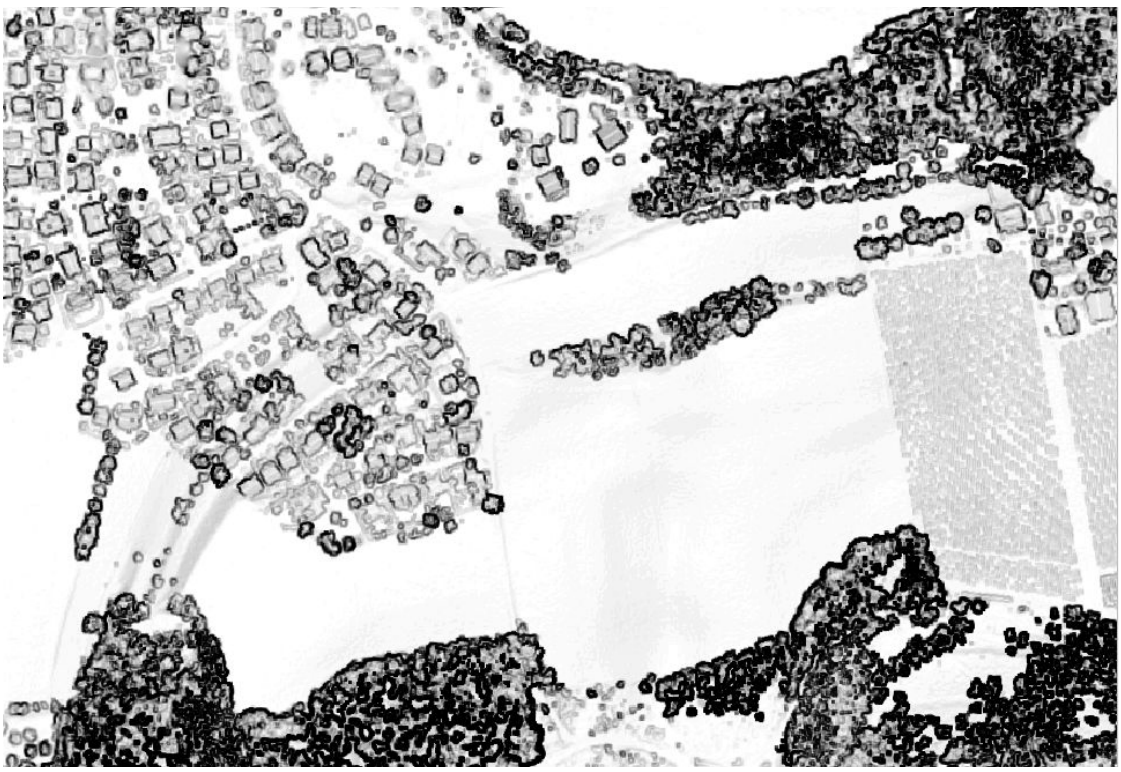


Figure 6.5: Standard deviation of the heights

directions.

$$lc = max(|\delta g_i|) \tag{6.3}$$
$$\delta g_i = \frac{\delta gr_1}{t} - \frac{\delta gr_2}{t} \tag{6.4}$$

where	i	=	the main directions (1..4)
	δg	=	gradient difference in a main direction
	δgr_1	=	gray value difference between the center pixel and the neighbouring pixel
	t	=	distance of the neighbouring pixel centers

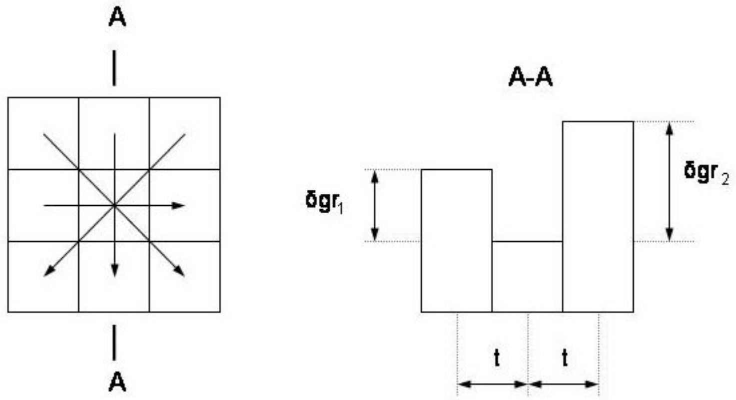


Figure 6.6: Local curvature computation. A 3x3 raster kernel can be seen. Arrows show the four directions of the gradient calculation.

The Laplace operator smooths as well, since it takes into consideration all values in the moving computation matrix, while local curvature omits the smaller values in order not to smooth the results. A filtered area by the Laplace operator can be seen in figure 6.7.

Border gradients

Artificial structures usually have at all sides abrupt rather than gradual height alteration, i.e. jumps at vertical walls.
The significant gradient is a gradient value over a certain threshold. The ratio of the number of these values and the number of all border pixels represents the border gradient feature.
The significant gradients along the border of segments contribute mainly to the discrimination of buildings/vegetation on one hand and terrain objects on the other hand. In the experiments of this thesis, while buildings and trees generally show a high amount of border gradients in laserscanning data (70% - 100%) most segmented terrain objects - even if sharp relief edges are included - have at least at some parts of the segment borders

Figure 6.7: Laplace filtered area

smooth transitions to the surrounding terrain model. Therefore, the amount of significant border gradients decreases below 50% in these cases.

Shape and size

The shape of segmented object areas may allows us to contribute to distinguish between artificial (man-made) objects (e.g. buildings, bridges etc.) and natural ones (e.g. trees, groups of trees, rough terrain or combination of both). For determination of shape parameters the contour lines of each segment have to be extracted. Because of working with segments of uniform (pixel) values and clearly defined borders a simple edge tracking algorithm can be applied to provide the 2D contour lines. After smoothing these lines, shape and size of these polygons can be analyzed.
Compactness *(C)* is a measure of the shape of the segment. It can be calculated as the ratio of the segment area and square perimeter:

$$C = \frac{A}{l^2} \tag{6.5}$$

Roundness *(R)* represents the same ratio. It is defined as:

$$R = \frac{4 \cdot A \cdot \pi}{l^2} \tag{6.6}$$

where l is the perimeter and A is the segment area. The R value is between 0 and 1, 1 corresponds to a circle, 0 is a segment without area and perimeter. It could be profitable to

distinguish trees from other objects, but in the practice, trees are also not perfectly circle shaped, therefore, the classification on compactness fails. Former investigations (Vögtle, Steinle, 2003) have shown that these commonly used standard parameters do not fulfill the requirements which are necessary to distinguish between the object shapes in this application.
For this reason, alternative parameters has been developed like geometry of the n longest lines, where at first the n longest lines of a contour polygon are selected (e.g. n=4). These lines are analyzed in terms of parallelism and orthogonality. A measure is calculated which is 100 for perfect parallel or orthogonal lines and decreases proportionally to increasing deviations from that. This shape parameter has proved to be suitable to distinguish between artificial and natural objects in most cases if their area is large enough. Small object sizes lead to ambiguities.
This parameter is obtained from the contour line of a segment. The usage of shape parameters is based on the assumption that artificial objects show more regular shapes than natural objects. Buildings have usually straight borders that are in a - more or less - parallel or orthogonal relation with each other, while vegetation outlines are irregular.

As it is already mentioned, first of all the contour lines must be extracted for the shape parameter calculation. On raster basis the outlines are not straight depending on the direction of the line, therefore, they must be generalized e.g. by the Douglas-Peucker method (Douglas, Peucker, 1973). Such extracted lines can be seen in 6.8. Details about the line extraction can be found in Steinle (2005). Buildings are limited usually with relatively long straight lines, while natural objects do not show such regularity.

Some simple rules can be stated about the segment size as well. The extreme small or large size of a segment may exclude some classes in the classification process. While terrain points can form arbitrarily large segments, buildings and vegetation have a naturally limited extent. Segments above a certain size may be terrain objects. Very small segments on the other hand, are probably vegetation parts. In addition, very small segments can not be classified reliably, because the features can not be extracted so precisely neither on the base of raster nor on point clouds. Definition of 'very large' or 'very small' in the parameterization is not easy, since it depends on the characteristic of the landscape.
The reliability of shape parameters depends on the extent of the segment, because larger segments enable a reliable extraction of shape parameters. Therefore, shape parameters can be weighted in the classification process.

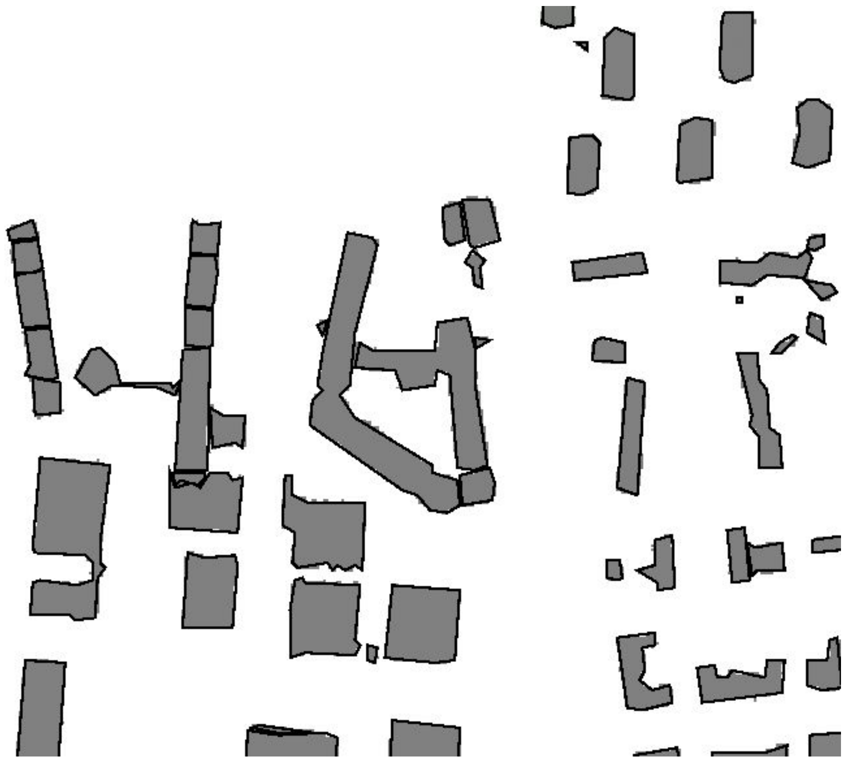


Figure 6.8: Extracted vectors of border lines

6.4.2 Radiometrical features

Intensity

Most ALS systems are able to measure and record the backscattered energy of the emitted laser pulse. Since the measured intensity depends on the sensor to object distance, the intensity values have to be normalized by an average distance. The intensity value is equal to the emitted power divided by the squared distance.
The diameter of laser beam on the ground may be 40-100 cm depending on the flying height and the beam divergence. Due to this size, the reflecting object may be smaller than the illuminated area, so we have to consider partial reflection in this case. It is easy to see that the measured intensity also depends on the size and reflectivity of the illuminated object. Both of these are unknown, moreover independent from each other. Since we know neither the reflectivity nor the size of the illuminated object, they can not be deduced from the measurements.
However, most systems record two reflections, so therefore we must consider more echoes. In principle, the sum intensity of these multiple echoes represents the total illuminated surface. In practice, not all of the reflections have enough power to be detected and measured. Moreover, the loss of energy caused by the atmosphere and the dispersion and absorption by the reflection are also unknown. Therefore, we can not calculate the reflection of different illuminated objects within the same footprint from the measured total intensity.
The only way to utilize intensity is to analyze the flat homogeneous surfaces. A more

elaborated paper is issued about the principles of intensity measurements by the TopoSys company (Katzenbeisser, 2002).

The reasons of the significant inhomogeneity and high noise of the intensity data are presented. We can analyse the intensities within the segments in an empirical way as well. In order to exclude extreme values, the median value may be taken from the intensity values within a segment. Vegetation contains many small illuminated surfaces in different elevations, which cause multiple echoes. Therefore, the reflected energy is divided into small amounts, so the measured intensity values are very low. In the case of buildings such an obvious rule can not be observed. Depending on the material and slope of a roof, they can show either high or low intensity values (see figure 6.9).

For one test site in the experiments, laser intensities were available which are recorded by the TopoSys II sensor. This additional information was also included in the investigations. The intensity of laser pulses depends highly on the characteristic of the reflecting material. In most cases buildings with commonly used rooftiles cause much higher or in the other case nearly the same intensity values as vegetation (figure 6.9).

Figure 6.9: Intensity data

Spectral data

Some of the laser scanner systems have additional devices to acquire spectral information, like RGB line scanners or video cameras. These enable simultaneous image capturing.
Statistical values, like average or median of spectral data within a segment could be applied in the classification process.
Although, spectral features of small objects are usually constant, they are often not homogeneous within segments. Moreover, the material of the bare earth is also inhomogeneous, its color is not constant and it may differ from location to location. Artificial objects are usually limited in extent, and their material is homogeneous in most cases.
An important drawback of using these devices is that they strongly limit the data acquisition time, since these photogrammetrical techniques are utilizable only in daylight and in appropriate weather conditions. One of the most important advantages of ALS in contrast to photogrammetry is that it is less dependent on natural lighting and weather conditions. Simultaneous image capturing abolishes completely this property, which is not acceptable in some applications, like in disaster management where a fast data capturing is necessary. Therefore, simultaneous image acquisition is not always achievable. For this reason, further application of image data is stopped, however, given spectral information can support the classification (e.g. NDVI index for vegetation classification (Steinle and Vögtle, 2001). See fig. 6.10).

6.4.3 Topological feature

The proximity analysis of neighbouring segments is based on their topological relation. It assumes that segments higher than their neighbours are objects. Neighbouring segments on different levels can also be objects, therefore, a neighbouring segment on a lower level is not necessarily a terrain segment. The analysis of the position of the neighbouring segments should proceed from the lowest to the highest level in order to label first the terrain segments. On the basis of these terrain segments, the neighbouring objects can be labelled more reliably. Of course, there are special cases, which can not be classified using topological features, like courtyards or a low building part surrounded by higher building parts.
In Hofmann et al. (2002) among others this topological information is utilized to detect buildings, assuming that buildings do not have higher neighbour objects than themselves, except when they are located on a slope.
Sithole (2005) divides the dataset into equally wide profiles in three directions. Points are connected into line segments in every profile, when they are on the same surface. Segments are labelled in every profile according to their relationship to the neighbouring segments. A set of rules is applied for labelling, combining the profiles and classifying the segments built from the profile combination. Using profiles simplifies the proximity analysis and reduces the processing time.

Figure 6.10: NDVI index. High values are lighter and low values are darker. Vegetation is lighter than any other materials.

6.4.4 Segment to surface model relation

In the chapter of filtering, the advantage of using an explicit surface model has been presented. The use of a model of terrain makes it possible to take into consideration the relation between the segment and this surface. As the bare earth is assumed as a patchwork of continuous surfaces, surfaces over this patchwork are objects. Distance between terrain model and segment can be used in the classification. These distances can be computed point-wise, between every point of the surface and the terrain. Statistical values of this set of residuals like mean, median or n-th quantile can be calculated for each segment. As it is represented in chapter 4.1.6 by the segment based robust filtering, the most prosperous possibility is to take the 3rd quantile.
These residuals represent very similar characteristic as the segment heights over a normalized DSM. The function of the nDSM is to exclude the terrain influence in the height model, in order to allow the comparison of object heights.

6.4.5 Feature extraction

The aim of feature extraction is to determine a representative value of a certain feature to each segment. On raster domain, this task is usually not too complicated. The segment is used as a mask on the feature image and from the feature values within the mask, one representative value is calculated. This representative value is calculated in a statistical way. Maximum, minimum, mean or median of the values can be calculated. In most cases, the average is used.
The borders of the segments usually have different characteristics to their internal areas, caused by their uncontinuous surface at the connection of neighbouring segments. Therefore, values at the segment borders are not considered in the computation in order not to use improper information. Height differences, local curvatures and standard deviation values can be dissimilar at the borders for example, so these values should not be considered.

Feature extraction in point cloud

However, it is more simple to interpolate points to a regular grid and use image processing tools on it, feature extraction can also be implemented on point cloud.
In Pfeifer et al. (2004), a point cloud texture algorithm is proposed that calculates texture either for a laser point, or for a point anywhere between the laser points. This solution allows computing the features over the whole area of the segment, but the extraction of the segment area without the segment borders is not solved. By dense point cloud, not only one line of measurements can hit an edge, but many points in multiple lines within a zone.

Because of this, to exclude points only at the segment borders is an inappropriate solution, therefore, points within a zone have to be left out.

6.5 Fuzzy classification

The purpose of classification is to assign unknown samples to exactly defined classes. Often, samples can not be unambiguously classified into one particular class, because the sample description does not fit completely for any class. It means, a sample may partially be member of more than one class. In spite of the fact that these samples are not classified into any classes, they should be put into the most appropriate class. We may assume that the sample belongs to that class, which definition fits the most for the sample.
A mathematical approach is necessary, whereby information and objects can be classified into more than one class. This is necessary for processing and modeling real occurrences. Subjective concepts can be processed by the fuzzy set theory invented by L. A. Zadeh.

Fuzzy models can work with continuous variants and in contrast to the traditional binary logic, partial and multi value truth can be handled. The use of fuzzy logic is especially advantageous, when the problem can not be solved easily due to the very complex processes. Robust systems can be built up that are able to operate error free with deficient or noisy data as well. Most of the applications are in the field of system control and automatization.

An exact description of segments from ALS data is difficult, because only discrete measurements are available for this purpose, which leads to loss of information. Usually each segment can be classified on the basis of one feature into more than one class.

The subsequent classification and its results depend on the preceding segmentation process because only segmented objects are classified. The fuzzy logic classification is based on the extracted features which have been described in section 6.4. Fuzzy logic presents an opportunity to get answers to questions with a truth value in a range of 0 and 1. The uncertain and often contradictory information can be handled and quite accurate results may be obtained. There is no boundary between membership and non-membership in the fuzzy theory. Therefore the elements can be not only members or non-members, but they can also have other level of membership. Fuzzy set is a function that sets a value of membership degree, which can be from 0 to 1. Zero membership indicates that the value is not in the set and value one shows that the sample perfectly represents the set. Degree of membership can be presented by a so called membership function (Fig. 6.11).
This uncertainty of classification parameters (features) can be modeled by the membership functions. It means, a relative accurate knowledge is necessary about the attribute values' membership degree in all classes. This may seem to be a difficult task, because of the relative high number of attributes and classes, but in reality, an experienced operator is able to approximate them. Besides this, parameter sets, namely the membership functions can be applied on more datasets as well, when they have similar topographical characteristic.
When an object can be unambiguously classified on the basis of one attribute, i.e. the degree of membership is one, the ambiguity or fuzziness is minimal. It means as well that the cut of the membership functions of the different classes is an empty set. If an object

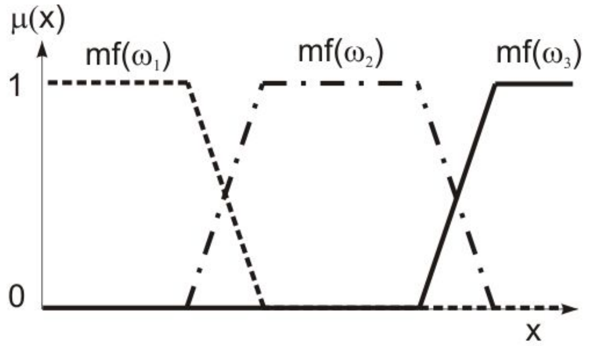


Figure 6.11: Membership functions of three classes (ω_j) for a feature

may equally be a member of two classes, than the ambiguity or fuzziness is maximal. Between these two extreme values, the degree of ambiguity varies.
So, the user has to define such a membership function for every parameter and every class (fuzzification). They may be built up by straight line sections in order to make the computation easier, but also functions of higher degree can be defined depending on the respective application. Normally, membership functions are defined in an empirical way by means of training samples visually selected and interpreted by an operator.

Histogram analysis may help to determine the parameters of membership functions, but a control and - if necessary - an improvement of these functions should be done in every case. These membership functions have proved to be quite stable and robust independent from different locations (Voegtle, Steinle 2003).

Fuzzy decision making systems are usually regulated by strict rules, but the system algorithms can be selected relativly freely. Although, widely used methods like the Mamdani- or Sugeno-methods can be used in a lot of applications, usually not only one certain method can solve a problem (Sugeno, 1985, Mamdani, 1975). The following decision making system is a simple and fast method for clustering objects on the basis of their features.
A concrete value of feature i leads - by means of the corresponding membership function - to the related degree of membership $\mu_i^{\omega_j}$ for every class ω_j. In our object classification experiments $j = 1..3$ (buildings/vegetation/terrain). All membership values for the same class j have to be combined for a final decision (inference process). The original Zadeh-type operators are used, such as minimum, maximum and product, besides these a weighted sum is tested as well. The minimum, maximum and product operator for a class can be defined as:

$$\mu_{(A\cap B\cap C)}^{\omega_j}(x) = min(\mu_A^{\omega_j}(x), \mu_B^{\omega_j}(x), \mu_C^{\omega_j}(x)) \tag{6.7}$$
$$\mu_{(A\cup B\cup C)}^{\omega_j}(x) = max(\mu_A^{\omega_j}(x), \mu_B^{\omega_j}(x), \mu_C^{\omega_j}(x)) \tag{6.8}$$
$$\mu_{(A\cdot B\cdot C)}^{\omega_j}(x) = \mu_A^{\omega_j}(x) \cdot \mu_B^{\omega_j}(x) \cdot \mu_C^{\omega_j}(x) \tag{6.9}$$

where A, B, C = extracted features,
ω_j = the class j, and
$\mu_A^{\omega_j}, \mu_B^{\omega_j}, \mu_C^{\omega_j}$ = degree of membership of the features for class j.

For the minimum operator the value of the result is defined by the minimum value of the used features which is the logical AND implementation in fuzzy environment. Similarly, the maximum value of all used features determines the value of a class by the maximum operator. This operator is used in fuzzy as logical OR. For these two operators, the fuzzy sets of the classes should constitute complementary membership functions, so the sum of the degrees of membership for every feature value should be 1. Therefore, the elements are classified into non-correlated classes and all features are taken into consideration with the same importance.
In cases where the sum of the degrees of memberships in a certain feature is more than 1, the accordant feature plays a more important role in the calculation. It would also mean in an extreme case that a sample is certainly a member of two or more classes. For the calculation of a weighted sum, an individual weight is assigned to each feature. This weight may be constant to express the reliability of a certain feature. However it can be also a function of another feature. For example, the shape parameter *'geometry of n longest lines'* expresses the parallelism and orthogonality of these lines. The reliability of this feature depends on the size of the object. It can be observed that this feature provides more reliable values if larger segments are concerned while at smaller segments only short contour lines can be extracted which leads - due to noise and rastering effects - to increasing deviations from parallelism and orthogonality. Therefore, small objects get low weight and extended objects get higher weights (see Fig. 6.12).

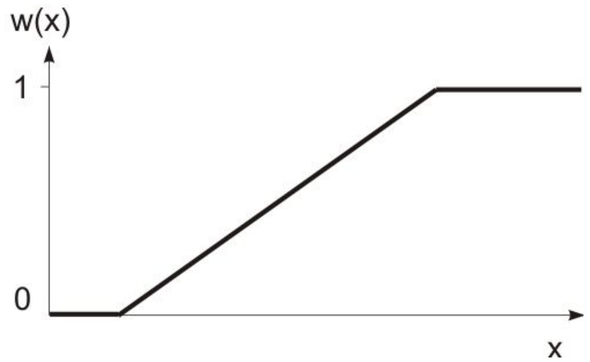


Figure 6.12: Weight function for the shape feature

The inference procedure results each segment and class in a crisp value that is not a function, but a real number. In every case the final decision is based on the maximum method, i.e. a segment will be assigned to the class of the highest probability. As an example for the obtained classification results the confusion matrix for the product operator is shown in table 6.1. Two test sites have been investigated, an urban area, and a rural one. In table 6.2 the results obtained by different inference operators are assembled for these two test sites. Classification rates in the table show the ratio of the number of correctly classified and the number of all objects in a class. It is obvious that the results are dependent on the respective operator. Using a combination of all available features the minimum and particularly the maximum operator provides results of lower classification rates. For the rural test site, this tendency is more significant than for the urban test site. Product and weighted sum method achieve higher classification rates of similar dimension. Other combinations, where not all features were included, lead to increasing differences.

Product	Building	Vegetation	Terrain
Building	95	5	0
Vegetation	4	96	0
Terrain	0	7	93

Table 6.1: Confusion matrix of classification rates [%] for the product operator (Rural test site)

	Urban	Rural
Product	90	95
Weighted sum	90	94
Minimum	88	64
Maximum	87	74

Table 6.2: Classification rates [%] by different operators in fuzzy logic

Due to this quality assessment of different inference operators, the product has been selected as a standard operator for subsequent investigations. To compare the reliability of the defined features and to demonstrate the influence of each of them, 9 different feature combinations have been calculated and the influence of missing features has been observed, where the independence of the features was assumed.
Correlated features may not improve the classification reliability, because they bias the computation, and give more weight for the correlated feature. The origins of miscellaneous features can be seen in table 6.3.

The feature combinations and their results can be seen in table 6.4 and 6.5. Besides the individual class-related values also an overall classification rate has been included. The results show (last row in table 6.5) that the amount of significant border gradients which should separate terrain objects has evidently no influence on the results in the urban test site. Comparing first/last pulse differences and height texture which both contribute to distinguish between buildings and vegetation, it is obvious that height texture is of less importance because the averaged improvement of classification rate is only about 1% to 3%. For first/last pulse differences this value is about 7% to 10%. Adding the shape parameter to the feature combination - only at the urban test site -, a slight improvement of the results (about 2%) can be observed due to the higher amount of larger buildings compared

Feature	Origin
Echo difference	First pulse and lust pulse vertical coordinates
Height texture (Laplace, local curvature)	Last pulse pixel proximity
Standard deviation	Last pulse sub pixel vertical coordinates
Border gradient	Object shape and height
Shape	Object shape
Intensity	Material, surface smoothness
Size	Object extension

Table 6.3: Origins of the features

to the rural region. The intensity values - only available for the rural test site - contribute significantly to the classification success. An increase of about 7% was achieved. In the last row, we can recognise that the shape parameter can improve the vegetation classification.

Border gradients	Height texture	Fp/lp differences	Shape	Laser pulse intensities	Class. rate buildings	Class. rate vegetation	Class. rate terrain	Overall class. rate
+	+	+	+	+	95	96	93	95
+		+	+	+	93	96	80	92
+	+		+	+	84	79	87	84
+	+	+		+	96	88	93	94
+			+	+	85	67	73	80
	+	+	+	+	93	96	80	92
		+	+	+	83	96	93	87
+	+	+	+		89	79	93	88
+	+	+			93	38	93	81

Table 6.4: Feature combinations for the rural test area

The users need to have extensive and accurate knowledge about the characteristic of the defined class elements. The classes can be determined by the membership functions. Their shapes can be described by parameters. Considering the number of classes and features, their number can be quite high. These parameters describe the shape of the membership functions. Moreover, we have to take into account the unique characteristic of each dataset and each scanning system, which may lead to slightly different features of

Border gradients	Height texture	Fp/lp differences	Shape	Class. rate buildings	Class. rate vegetation	Overall class. rate
+	+	+	+	89	90	90
+		+	+	93	85	89
+	+		+	86	80	83
+	+	+		88	86	87
+			+	91	62	78
		+	+	90	89	90

Table 6.5: Feature combinations for the urban test area.

segments and variable parameter sets. Even if the system and the point density is constant, parameter sets may not be applicable on different types of topography. Small houses in a rural area have a different characteristic compared to large buildings in a city or in an industry area. Therefore, both kinds of object features must be contained in the parameter set.

6.6 Maximum likelihood classification

In order to evaluate the results of the fuzzy classification, 2 datasets are also classified with a well known standard statistical classification method.
The maximum-likelihood method is a widely used supervised statistical classification method. It is based on the assumption that there are statistical models that describe the distribution of the classes in the feature space. A classification problem can be solved optimally, if we know the prior probabilities ($p(\omega_j)$) and the probability density function ($p(x/\omega_j)$). Unfortunately, in the most cases, we do not have this complete knowledge about the probability. Therefore, samples are used to estimate the probabilities and probability densities and than these estimated values are used as if they were the true values. The problem of parameter estimation can be approached by the maximum-likelihood estimation. This method views parameters as fixed but unknown values. The best estimation of these values is one, which maximizes the probability of obtaining the observed samples. In other words, these values make the observed data most likely.
The likelihood Lk is defined as the a posteriori probability of an object belonging to class j (Duda, Hart, Stork, 2001).

$$Lk(X) = p(\omega_j/x) = p(x/\omega_j)p(\omega_j)/\sum_{i=1}^{m} p(\omega_i)p(x/\omega_i) \tag{6.10}$$

where	$p(\omega_j)$	=	a-priori probability of class j
	$p(x/\omega_j)$	=	conditional probability to observe x from class ω_j or probability density function

Lk depends on $p(x/\omega_j)$ or the probability density function. For mathematical reasons, a multivariate normal distribution is applied as the probability density function. In the case of normal distributions, the likelihood can be expressed as follows (Bähr, Vögtle, 1999).

$$p(x/\omega_i) = \frac{1}{\sqrt{(2\pi)^n\,|C_i|}} exp\left(\frac{-(x-\mu_i)^T C_i^{-1}(x-\mu_i)}{2}\right) \tag{6.11}$$

where	n	=	number of features
	x	=	feature vector
	$p(x/\omega_i)$	=	likelihood of x belonging to class i
	μ_i	=	mean vector of class i
	C_i	=	variance-covariance matrix of class i
	$\|C_i\|$	=	determinant of C_i

The n-dimensional covariance matrix is composed of the variances and covariances between the n-channels:

$$C_i = \begin{pmatrix} \sigma_{11} & c_{12} & \dots & c_{1n} \\ c_{21} & \sigma_{22} & \dots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \dots & \sigma_{nn} \end{pmatrix}_i \tag{6.12}$$

$$\sigma_{ii} = E((x - \mu_i)^2/\omega_i) \tag{6.13}$$

$$c_{ij} = c_{ji}$$

In the case of Maximum-likelihood classification, each class has an individual covariance matrix and mean vector. The separation of classes is defined by curves in the case of more than two classes. To obtain reasonable results in the investigations, exactly the same training and control objects have been used in this classification. The method is used as a standard image processing tool.

In order to evaluate the classification methods, some experimental results of the comparison are presented in the followings. The results for two test sites (an urban and a rural site) - based on the combination of all features - are assembled in table 6.6. For reasons of comparison also the main classification rates of fuzzy logic are included in this table.

Method	Test site	Class. rate buildings	Class. rate vegetation	Class. rate terrain	Overall class. rate
Fuzzy logic	Rural	95	96	93	95
Maximum-likelihood	Rural	96	96	93	95
Fuzzy logic	Urban	89	90	-	90
Maximum-likelihood	Urban	92	86	-	89

Table 6.6: Comparison of main classification rates between fuzzy logic and maximum-likelihood method

It is obvious that classification rate of vegetation in the urban test site is a bit higher for fuzzy logic than for maximum likelihood but with regard to buildings, the total classification rate is the same. These tiny differences are caused by the influence of the definition of membership functions in the fuzzy logic approach. Even a modification of the related membership functions in order to increase the classification rate of buildings would inevitably lead to an accordant decrease of classification rate for vegetation, so the resulting overall classification rate would remain nearly the same. The results of both methods are in the same dimension if all available features are used. If combinations of only a few feature are applied no definite assessment can be made. However there is no significant differences in the results, the advantage of fuzzy logic may be that the transferability to other locations seems to be easier especially for applications where only a few training areas/objects are available due to its robust membership functions.

6.7 Vegetation detection

As it was mentioned above, not all vegetation objects can be segmented and classified by the proposed method. Vegetation without foliage causes the bulk of last echoes to be backscattered from the ground. It means that the segmentation and classification of vegetation exclusively from last pulse data is not suitable.

In the first pulse data, the upper surface of vegetation has in most cases an irregular shape, therefore, segmentation acquires only relatively smooth parts of vegetation objects, due to the concept of detecting all buildings as far as possible. The segmentation of plain surfaces (see chapter 5.3.1) can not provide suitable results in vegetation segmentation, since the canopy is divided into several very small segments or no segments can be acquired. The object segmentation method (see chapter 5.4) can only segment objects, where the height difference of neighbouring points is under a certain threshold and the heights in the nDSM are above an other threshold (e.g. 2m). These requirements are not fulfilled in the case of vegetation, on one hand because of the high possible differences of neighbouring point heights and on the other hand, because last pulse measurements may be backscattered from a very low level of the vegetation or even from the terrain. Therefore, vegetation can be segmented only partly by this method. In case the first pulse data are segmented with this method, then the vegetation and building objects that are standing close to each other are not separated i.e. they are merged in the same segment. These segments, which contain more type of objects cause misclassification, therefore this solution is also not sufficient in every case. These problems of vegetation detection can be solved by the use of first and last pulse differences.

Normally, trees do not appear completely in the last pulse DSM, but the first/last pulse differences are much higher there than in the case of buildings or terrain objects (see 6.4.1). However, building edges can cause a similar effect, namely, relative high first and last pulse differences, but they appear as lines while vegetation objects appear as patches. Since the buildings are already classified in the previous steps of the segmentation and classification process, it is possible to mask out the building edges from the height difference data. Building segments from last pulse data are systematically smaller than their real extent and even smaller than in the first pulse DSM. Therefore, the classified building segments are increased in respect of the size obtained by the described region growing method.

Different rasterisation methods were applied to first and last pulse data sets, in order to achieve the highest height difference within a raster. Because of this, only the height differences above 1m are taken into consideration, the smaller differences may be caused by the rasterisation. Figure 6.13 shows the result of the fuzzy classification and vegetation detection.
After this step the height differences show locations of the less dense vegetation and possibly overhead power lines. In consequence of their shape, power lines can be filtered

out with a morphological process (opening).

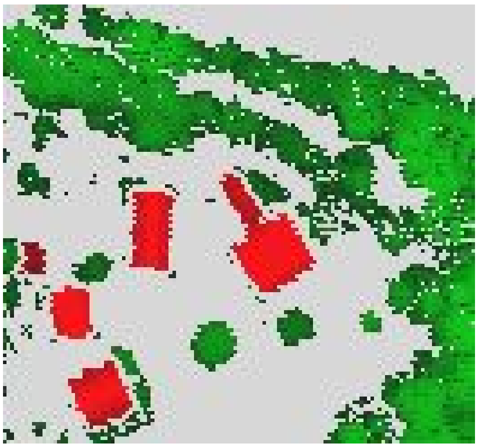


Figure 6.13: Classified buildings and detected vegetation

This method does not directly provide vegetation segments, but pixels. The detection of vegetation is a preprocessing step for its segmentation. After the generalization of the various vegetation species, a mathematically describable form may approximate the various vegetation classes (e.g. conifers, deciduous trees). This mathematically defined shape can be adjusted to the measurements. The precondition of this modelling is the segmentation of points that belong to the same tree. For this purpose, methods like watershed algorithm can be used. Firstly a smoothing filter is used in order to avoid the separation of small canopy parts. Former investigations show that after this smoothing, a canopy of one single tree may still be separated into more segments. Furthermore, different canopies with smooth transition between them may be merged into one segment. This limitation can be only solved by the use of additional data, like terrestrial laser measurements. Some single tree extraction methods can be seen in the literature, e.g. Straub (2003), Weinacker et al. (2004). In figure 6.14, vegetation segments are presented, created by the watershed algorithm. In this case the detected first pulse points are preprocessed by a Gaussian filter in order to smooth the vegetation surface. In forestry applications, these segments can be used for e.g. tree trunk estimation and vegetation modelling. This small example shows minor reliability of the single tree segmentation, while the segments have sometimes a shape that can not represent a real canopy.

6.8 Discussion

The existing segment based classification methods usually apply geometrical or topological features. The presented object classification method is very elastic. The available extractable features are determined by the data characteristic. Geometrical, topological, and also radiometrical information can be entered, if available.

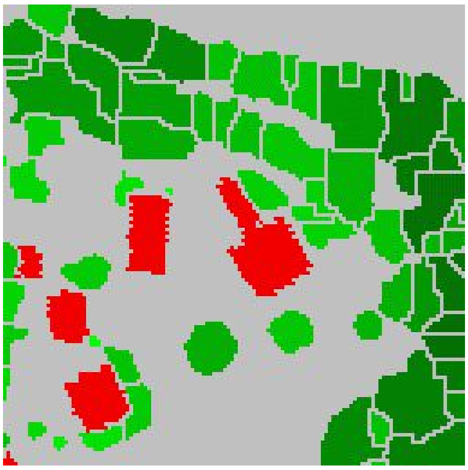


Figure 6.14: Vegetation segmented by watershed algorithm

The classification method can also be selected according to the users' demands. Maximum-likelihood method offers a supervised classification, where the operator has to train the algorithm for the classification by indicating typical samples of a class. Fuzzy logic offers a supervised classification too, where the operator uses the a-priori knowledge about the features of the classes and determines the membership functions for each class and feature. One can see that the former approach has to be trained in advance and then it works automatically. Additionally the training is necessary in every site. This repeated task can slow down the data processing in case of a large number of sites. The latter approach (Fuzzy method) better enables us to consider the knowledge of the human operator. However, the determination of the membership functions takes a relatively long time, the parameter sets can be applied on all sites and, therefore, this time pro site become relatively short in case of a large number of sites. Fuzzy classification offers a high processing elasticity, the decision making can be adjusted to a particular task. Four inference operators have been investigated and two of them have turned out to be suitable for the task and, of course, it is not out of the question that even more suitable solutions exist.

In case the classification of an entity is uncertain, i.e. more than one class has almost the same probability, the entity can be indicated as 'uncertain'. The classification of the 'uncertain' objects can be checked by the operator.

The results of object classification depend on the quality of segments. Undersegmentation can confuse the classification, since the extracted features are derived from more object types, which provide ambiguous data.

The vegetation detection works on the pixel basis. Segmentation of vegetated regions would be possible taking into account the first and last pulse differences, but it would not provide better results than the pixel based method.

Chapter 7

Experiments and results

7.1 Segment filtering

In order to examine the filtering performance of the segment based robust interpolation, a test data set has been chosen. Within a project on laser scanning, the OEEPE "Organisation Européenne d'Etudes Photogrammetriques Expérimenteus" (The European Organization for Experimental Photogrammetric Research; since 2002 European Spatial Data Research (EuroSDR)) entrusted the Fotonor AS (today Blom Geomatics AS) to acquire two test areas. These data have been submitted for research purposes free of charge. In 2002, an international filter test has been announced with the title "ISPRS test on extracting DEMs from point clouds: A comparison of existing filters". This comparison has been carried out and the results have been presented by George Sithole and George Vosselman on a web site (http://enterprise.lr.tudelft.nl/frs/isprs/filtertest/). Eight test sites were chosen in the area of Stuttgart and Vaihingen-Enz (Germany). The aims of the comparison were:

1. "To determine the comparative performance of existing filters - one feature of filters is that they are not universally applicable
2. To determine the sensitivity of filtering algorithms under varying point densities.
3. To determine problems in the filtering of point clouds that still need further attention."

Although the comparison was finished in 2003, the available data sets and reference data as well as the detailed description of the comparison enable us to evaluate new filters. The data has been provided by an ALTM rotating mirror scanner, which is able to measure with 10 kHz pulse repetition rate. In the urban area of Stuttgart, the point density is around 0.67 $points/m^2$ and in the rural area of Vaihingen it is about 0.18 $points/m^2$.

As a base for subsequent comparisons, the reference data set was filtered manually by George Sithole and available on the ISPRS filter test website. The experienced operator has decided, if a point belongs to the terrain or if it is an object point (see Sithole, 2005). The relative low point density leads to difficulties also in the manual interpretation, since some points can not be classified unambiguously into the terrain or object classes. In some

cases, especially in urban areas laser scanning can not provide enough information for a perfect classification.
Description of the test samples and the filtering difficulties can be seen in the ISPRS filter test documentation (see above).

7.1.1 Segmentation for terrain extraction

The main goal of the segmentation is to produce homogeneous segments. Therefore, the parameterization of the process aspires to provide approximately plane surfaces and the size and number of fragments is less important (see chapter 5.3.1). The parameters of segmentation are adjusted to the characteristics of the data set, which is mostly influenced by the point density.
Since the point distribution in the flight direction is approximately equal to the perpendicular direction in the ISPRS dataset, the n number of neighbours can be relative small. In this case $n = 8$ provides neighbouring points usually within a circle. The similarity of normal vectors (α) has been chosen relatively high ($\alpha = 20°$) with the aim of connecting points to the terrain segments that are near to break lines and edges. The distance of the candidate point to the adjusting plane (r) is 0,25 m and the distance between the current point and the candidate point (d) is set to 4 m. The produced segments are checked by visual inspection whether they contain mixture of points or not.

7.1.2 Filtering

The process of filtering can be managed by a relative high number of parameters and the determination of parameters for each site would cause a loss of time. Therefore, all the sites have been filtered by the same parameter set. In the robust filtering 4 iteration steps were carried out (see chapter 4.1.6). The surface model is *moving least squares* with an adjusting plane (parameterized over XY). All points are used within a circle of 11 m radius. Weight function has a halfweight of 1, 0.8, 0.6, 0.4 meter in the different iterations. The idea is to get a surface that gradually features more and more details and allows better fitting to terrain forms (e.g. break lines). For the robust error removal the representative filter value per segment was the 66% quantile of the individual filter values. The weight function decreases from 7, to 5, to 3, to 2.5, and the range of the weight function, -i.e. the distance over all the weights are set exactly to zero-, is 10.5, 7.5, 4.5 and 3.75, which is 1.5 times the halfweight. The a-priori accuracy of the points was set to 10 cm, which corresponds to the laser measurement height accuracy. This means that a segment with a residual of 10cm has a normalized residual of 1. Finally, all segments with the weights larger than 0.5 were accepted. A segmented sample and the terrain segments can be seen in figure 7.1. On the left side, all segmented points can be seen, while on the right side only the terrain segments are presented.

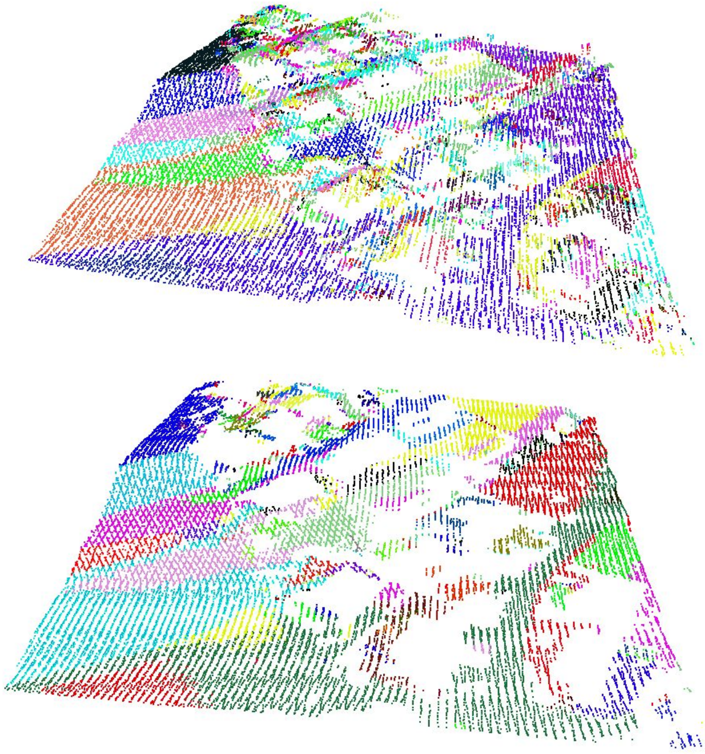


Figure 7.1: Segmented and filtered sample. On the top, the result of segmentation is presented. At the bottom, the resulted ground segments can be seen.

The filter results of the samples can be seen in figure 7.2-7.15. In each figure, on the left side, a shaded relief of the original dataset can be seen. On the right, the results of the filtering are presented by the original point cloud. Green and light blue represent the correctly classified terrain and object points respectively. Orange points show the type II errors, namely the misclassified terrain points and purple points are identical with type I errors, i.e. the misclassified object points.
A numerical evaluation of the filter results can be seen in table 7.2-7.15. Table 7.1 explains the abbreviations and numbers in the tables. These tables are presented in order to give a numerical comparison to filters which took part in the ISPRS filter test. The confusion matrices of each test site are presented. The type I, type II and total errors are presented in three diagrams as well (figure 7.18, 7.19). Type I errors are presented as a percentage of all terrain points. Type II errors are presented as a percentage of all object points, and total errors shows the misclassified points as a percentage of all points.
The results of the samples are discussed in the following.

		Filter result					
		Terrain	Object				
Reference	Terrain	**c.c.tp.**	nr.typeI	nr.tp.	tp.%	**Type I**	**typeI%**
	Object	nr.typeII	**c.c.op.**	nr.op.	op.%	**Type II**	**typeII%**
		nr.tp.f.	nr.op.f.	nr.p.		**Total**	**total%**
		tp.f.%	op.f.%			**Ov. acc.**	**ov.acc.%**

Table 7.1: Meaning of the single numbers in the tables

where	c.c.tp.	-	correctly classified terrain points
	c.c.op.	=	correctly classified object points
	nr.typeI	=	number of type I errors
	nr.typeII	=	number of type II errors
	nr.op.	=	number of object points
	nr.tp.	=	number of terrain points
	op.%	=	ratio of object points to all points in %
	tp.%	=	ratio of terrain points to all points in %
	nr.op.f.	=	number of object points in the filter results
	nr.tp.f.	=	number of terrain points in the filter results
	op.f.%	=	ratio of object points to all points in the filter results in %
	tp.f.%	=	ratio of terrain points to all points in the filter results in %
	typeI%	=	ratio of type I errors to the number of terrain points in %
	typeII%	=	ratio of type II errors to the number of object points in %
	total%	=	ratio of the sum of errors to the sum of all points in %
	ov.acc.%	=	overall accuracy (100%-total errors) in %

Sample 11: The first sample is the most difficult of all samples. The very steep, vegetated slope caused the problems for the filter. Type I errors occur the most frequently, since the low vegetation and the bare earth are undersegmented, therefore the residuals to the trend surface are high enough to omit the segment from the dataset. Overlapping regions between the stripes cause oversegmentation which leads to Type II errors. The number of Type I errors can be reduced by choosing segmentation parameters that prevent from undersegmentation. It would increase the oversegementation as well, so the number of total errors would not change significantly.

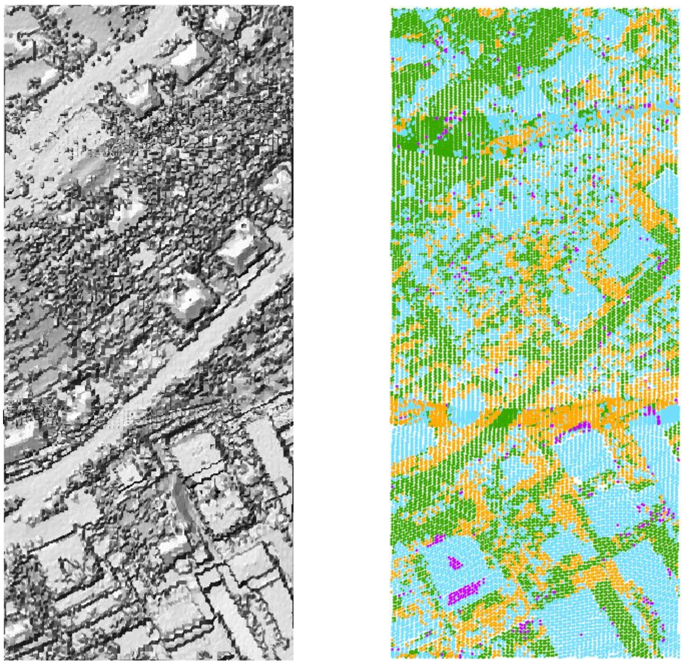


Figure 7.2: Sample 11. (Green - ground points, light bllue - object points, orange - type II errors, purple - type I errors)

		Filter result					
		Terrain	Object				
Reference	Terrain	**15211**	6575	21786	57.31%	**Type I**	**43.23%**
	Object	554	**15671**	16225	42.69%	**Type II**	**3.54%**
		15765	22246	38011		**Total**	**18.76%**
		41.47%	58.53%			**Ov. acc.**	**81.24%**

Table 7.2: Sample11

Sample 12: In this site, the most Type II errors caused -as in the first sample- by the oversegmentation in the overlapping regions. The continuous surface of the low vegetation leads to Type I errors.

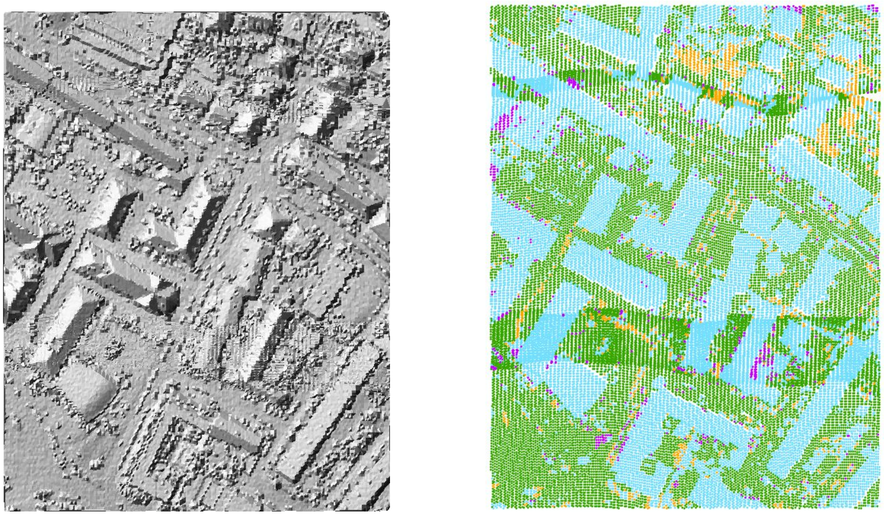


Figure 7.3: Sample 12

		Filter result					
		Terrain	Object				
Reference	Terrain	**24648**	2044	26692	51.21%	**Type I**	**8.29%**
	Object	918	**24510**	25428	48.79%	**Type II**	**3.75%**
		25566	26554	52120		**Total**	**5.68%**
		49.05%	50.95%			**Ov. acc.**	**94.32%**

Table 7.3: Sample12

Sample 21: In this sample a bridge was detected. The difficulty of the bridge detection is the smooth transition between the object and the bare earth. This transition between the objects can not be exactly detected by a plane segmentation method, which was applied. The ground and the bridge became undesegmented, causing many Type I errors. These errors are unpredictable, since the ground segment at the end of the bridge might end on the bridge, causing Type II errors instead of Type I errors.

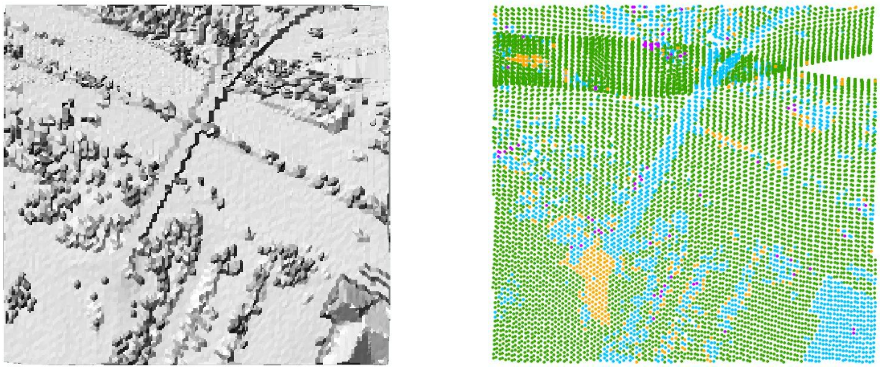


Figure 7.4: Sample 21

		Filter result					
		Terrain	Object				
Reference	Terrain	**9643**	443	10086	77.82%	**Type I**	**4.59%**
	Object	95	**2780**	2875	22.18%	**Type II**	**3.42%**
		9738	3223	12961		**Total**	**4.15%**
		75.13%	24.87%			**Ov. acc.**	**95.85%**

Table 7.4: Sample21

Sample 22: Large buildings and gangways are the difficulties in this sample. Large building roofs are oversegmented that causes Type II errors in the middle of the roofs. Gangways are relatively narrow, therefore, these segments are eliminated. They would not be misclassified, if they would be wider or the height differences between the levels would be smaller.

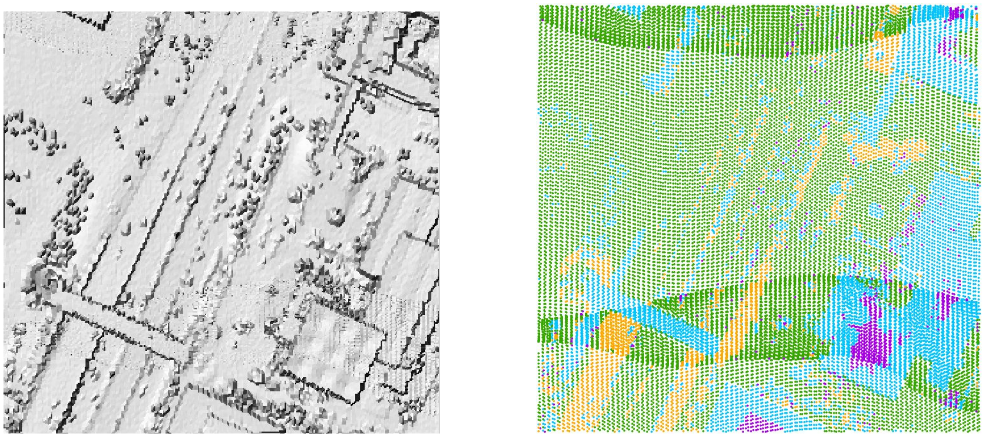


Figure 7.5: Sample 22

		Filter result					
		Terrain	Object				
Reference	Terrain	**19969**	2535	22504	68.80%	**Type I**	**12.69%**
	Object	1392	**8811**	10203	31.20%	**Type II**	**15.80%**
		21361	11346	32707		**Total**	**12.01%**
		65.31%	34.69%			**Ov. acc.**	**87.99%**

Table 7.5: Sample22

Sample 23: The speciality of the sample is the complex building with ramps. There are objects (stairways, ramps) in the buildings that can not be easily defined if they are bare earth or not. According to the ISPRS control data, some ramps are classified as objects instead of bare earth. I think, these ramps could be classified as objects as well and in this case the number of Type I errors would be significantly lower. Type II errors are caused mostly by the oversegmentation in the overlap regions as usual. The filter is able to preserve discontinuities due to the segmentation.

Figure 7.6: Sample 23

		Filter result					
		Terrain	Object				
Reference	Terrain	**11567**	1657	13224	52.69%	**Type I**	**14.33%**
	Object	851	**11021**	11872	47.31%	**Type II**	**7.72%**
		12418	12678	25096		**Total**	**9.99%**
		49.48%	50.52%			**Ov. acc.**	**90.01%**

Table 7.6: Sample23

Sample 24: This sample contains a narrow ramp (in the middle) that should be a part of the terrain. This filtermethod does not make any difference between bridges and ramps. The misclassified ramp causes Type I errors.

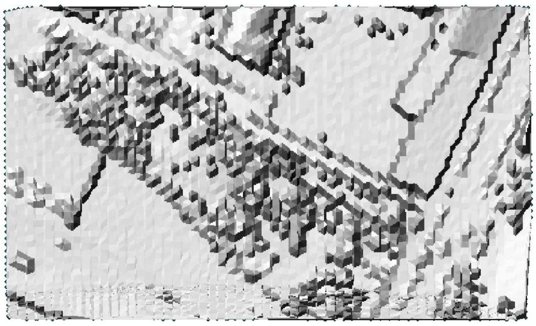
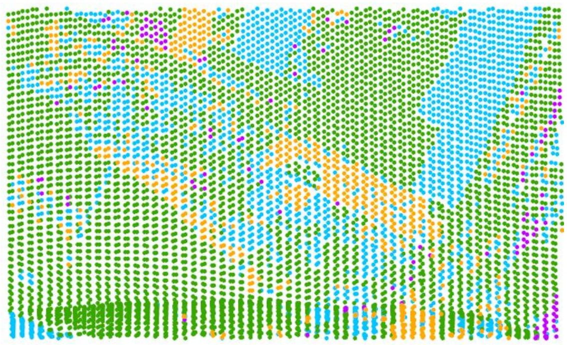



Figure 7.7: Sample 24

		Filter result					
		Terrain	Object				
Reference	Terrain	**4734**	701	5435	72.53%	**Type I**	**14.81%**
	Object	131	**1927**	2058	27.47%	**Type II**	**6.80%**
		4865	2628	7493		**Total**	**11.10%**
		64.93%	35.07%			**Ov. acc.**	**88.90%**

Table 7.7: Sample24

Sample 31: The segmentation based robust interpolation performs well on this relatively simple site. Only the oversegmentation causes Type II errors in the overlap regions.

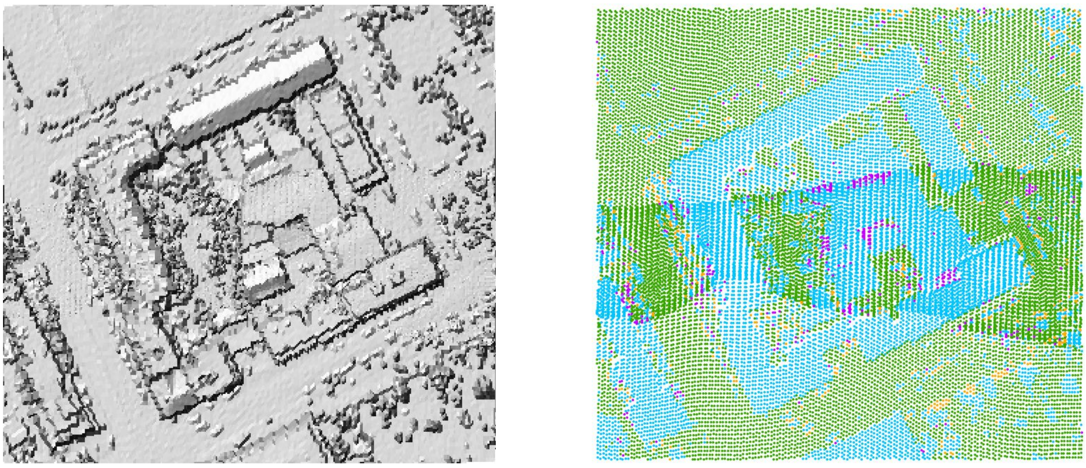


Figure 7.8: Sample 31

		Filter result					
		Terrain	Object				
Reference	Terrain	**15003**	553	15556	53.90%	**Type I**	**3.69%**
	Object	713	**12593**	13306	46.10%	**Type II**	**5.66%**
		15716	13146	28862		**Total**	**4.39%**
		54.45%	45.55%			**Ov. acc.**	**95.61%**

Table 7.8: Sample31

Sample 42: In this sample a railway station can be seen. There are different objects on different levels, which causes confusion in the filtering. Objects are the railway roof, the platforms and railway cars. Tracks are considered as terrain. There are higher level differences between the roof and railway car than between the railway car and the track. Therefore the railway cars are not filtered out and cause Type II errors.

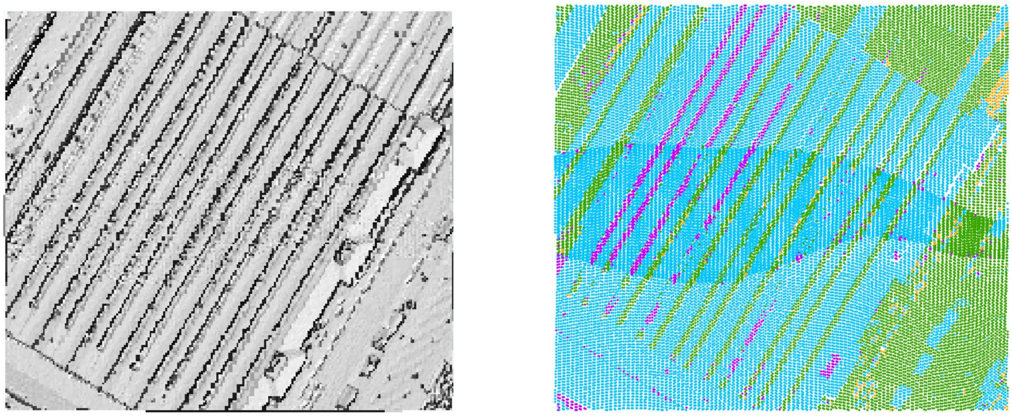


Figure 7.9: Sample 42

		Filter result					
		Terrain	Object				
Reference	Terrain	**12092**	351	12443	29.30%	**Type I**	**2.90%**
	Object	1914	**28114**	30028	70.70%	**Type II**	**6.81%**
		14006	28465	42471		**Total**	**5.33%**
		32.98%	67.02%			**Ov. acc.**	**94.67%**

Table 7.9: Sample42

Sample 51: This sample shows a vegetated slope. Detecting the lower vegetation is very difficult, because these are often undersegmented with ground points. Undersegmentation may cause Type I and Type II errors as well, depending on the ratio between the number of object and ground points. The larger objects are filtered well.

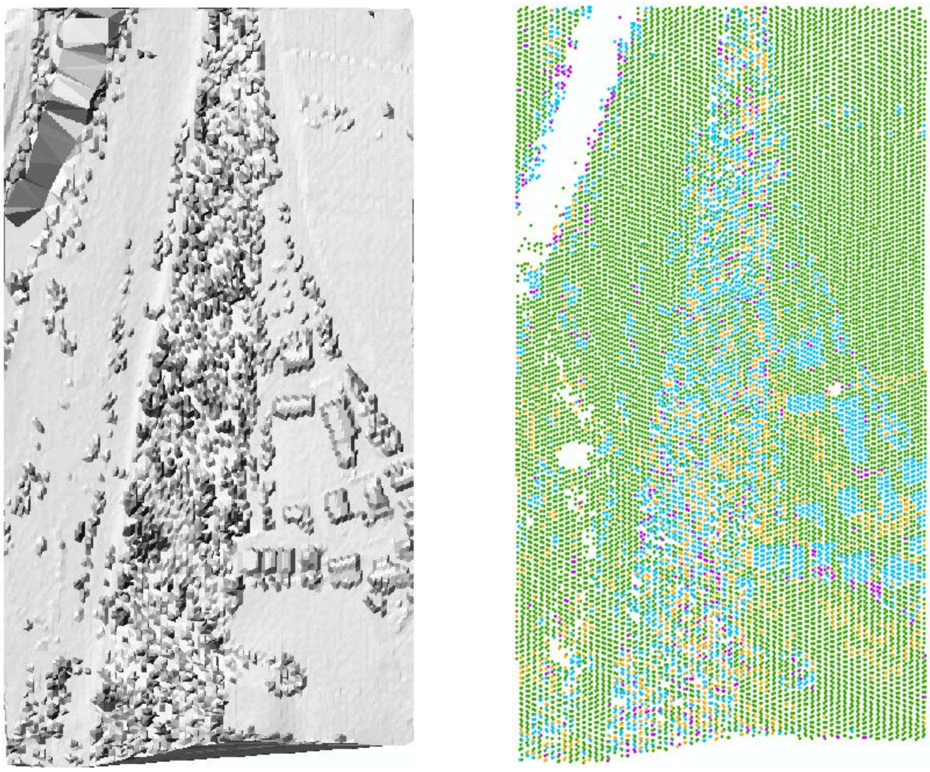


Figure 7.10: Sample 51

		Filter result					
		Terrain	Object				
Reference	Terrain	**12588**	1363	13951	78.17%	**Type I**	**10.83%**
	Object	446	**3449**	3895	21.83%	**Type II**	**12.93%**
		13034	4812	17846		**Total**	**10.14%**
		73.04%	26.96%			**Ov. acc.**	**89.86%**

Table 7.10: Sample51

Sample 52: Type I errors are caused by the vegetation on a steep slope as in sample 51. Type II errors on the upper right corner appear because of the border effect.

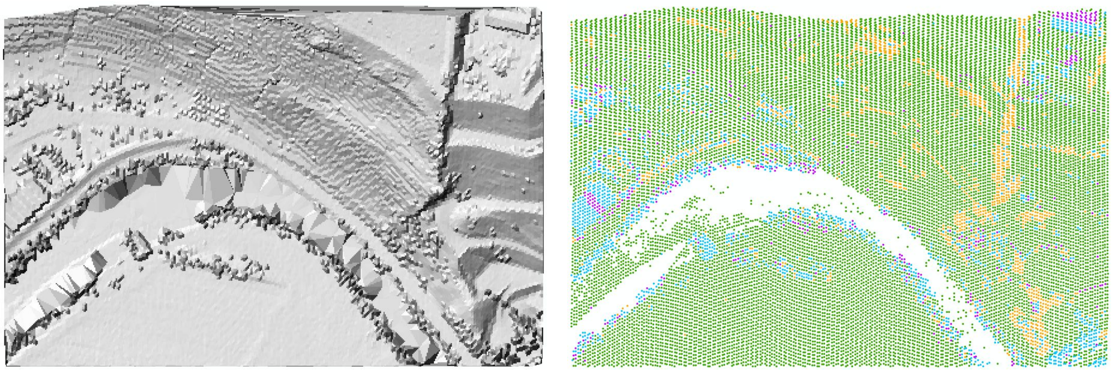


Figure 7.11: Sample 52

		Filter result					
		Terrain	Object				
Reference	Terrain	**18521**	1592	20113	89.49%	**Type I**	**8.60%**
	Object	446	**1916**	2362	10.51%	**Type II**	**23.28%**
		18967	3508	22475		**Total**	**9.07%**
		84.39%	15.61%			**Ov. acc.**	**90.93%**

Table 7.11: Sample52

Sample 53: This sample contains an open quarry. The segmentation based filter can not succeed in the edge preserving. The reason for this unfavourable effect is that the relatively narrow environment of the edges are segmented into one continuous segment. Since most of the points within the segment are close to the edge, the representative filter value is higher than allowed. Choosing a lower quantil of the residuals could help in this problem, however it would increase the number of Type II errors as well.

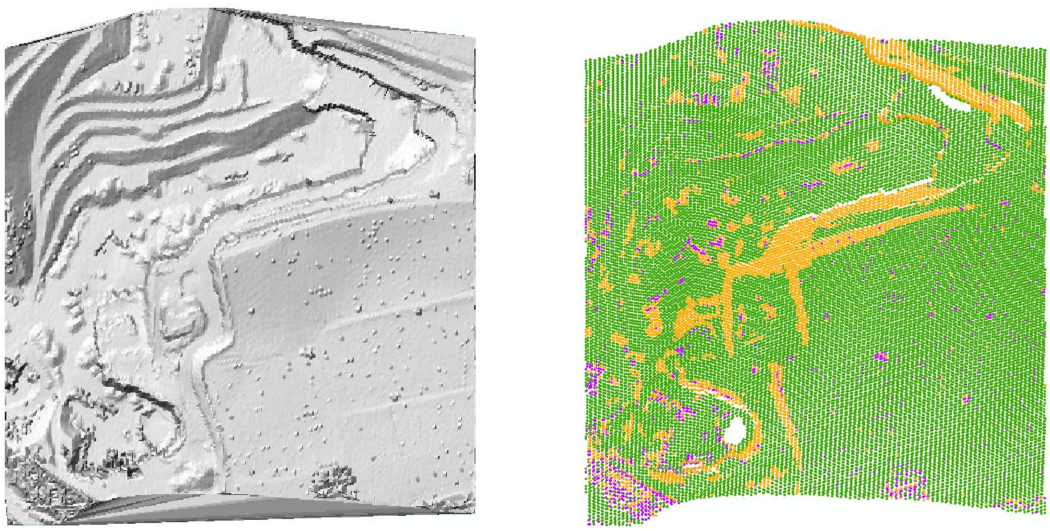


Figure 7.12: Sample 53

		Filter result					
		Terrain	Object				
Reference	Terrain	**28644**	4346	32990	95.96%	**Type I**	**15.17%**
	Object	241	**1148**	1389	4.04%	**Type II**	**20.99%**
		28885	5494	34379		**Total**	**13.34%**
		84.02%	15.98%			**Ov. acc.**	**86.66%**

Table 7.12: Sample53

Sample 54: This sample seems to be relatively simple, but the low point density, the low objects and the small objects make it difficult to filter. Low objects cause type II errors, and bare earth points near to objects cause type I errors.

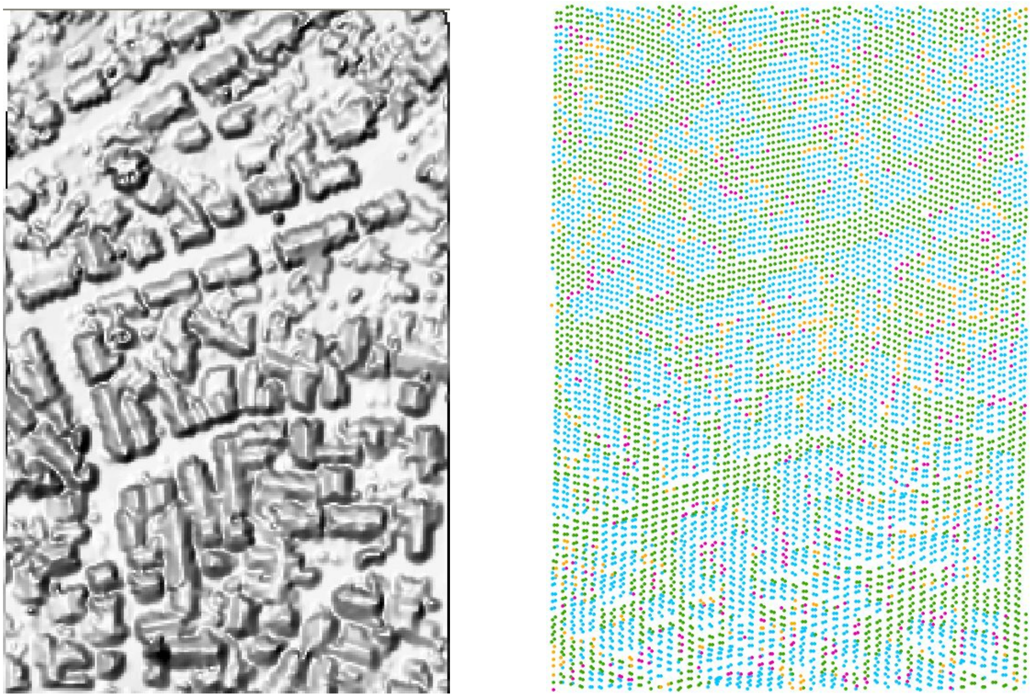


Figure 7.13: Sample 54

		Filter result					
		Terrain	Object				
Reference	Terrain	**3554**	430	3984	46.28%	**Type I**	**12.10%**
	Object	459	**4166**	4625	53.72%	**Type II**	**11.02%**
		4013	4596	8609		**Total**	**10.33%**
		46.61%	53.39%			**Ov. acc.**	**89.66%**

Table 7.13: Sample54

Sample 61: This sample contains relatively few objects. Type I errors occur on the road embankments. The undersegmentation causes only very few Type II errors, but more Type I errors.

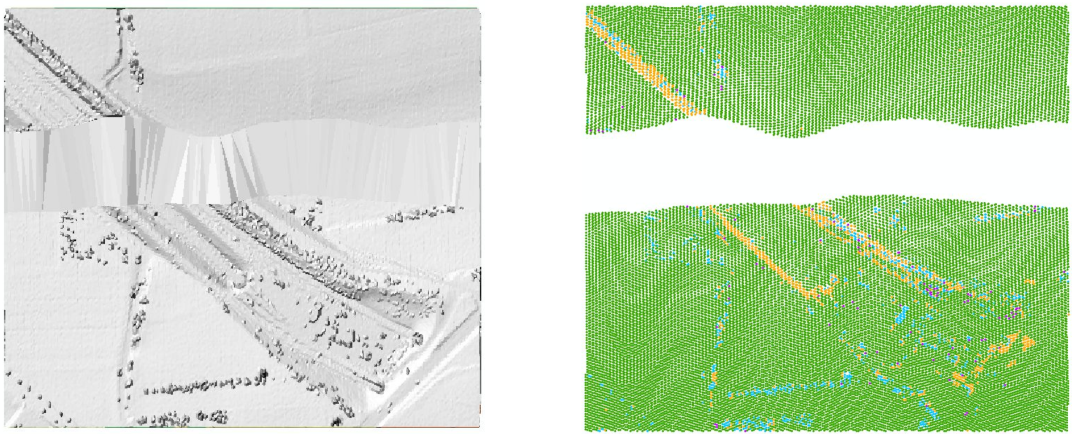


Figure 7.14: Sample 61

		Filter result					
		Terrain	Object				
Reference	Terrain	**32704**	1151	33855	96.56%	**Type I**	**3.52%**
	Object	100	**1106**	1206	3.44%	**Type II**	**9.04%**
		32804	2257	35061		**Total**	**3.57%**
		93.56%	6.44%			**Ov. acc.**	**96.43%**

Table 7.14: Sample61

Sample 71: This sample shows the problem that was mentioned at sample 21. The bridge and segment borders are not identical, therefore, the bridge contains Type II errors and the ground at the end of the bridge contains Type I errors. This kind of landscape would cause difficulties for every kind of point based and segment based filters.

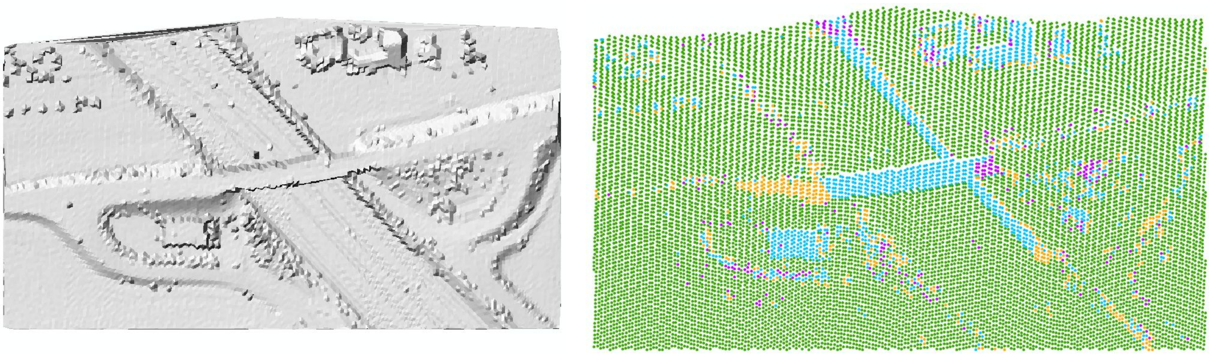


Figure 7.15: Sample 71

		Filter result					
		Terrain	Object				
Reference	Terrain	**13279**	597	13876	88.69%	**Type I**	**4.50%**
	Object	285	**1485**	1770	11.31%	**Type II**	**19.19%**
		13564	2082	15646		**Total**	**5.64%**
		86.69%	13.31%			**Ov. acc.**	**94.36%**

Table 7.15: Sample71

7.1.3 Segmentation evaluation

The filtering results are strongly influenced by the quality of segmentation, since point groups and not single points are filtered. All points in a point group are classified as object or as terrain, therefore, in case a segment contains object and terrain points, one group of these two classes within the segment will be misclassified.
The advantage of filtering segments over filtering points can be exploited if the size of segments reach a certain extent. In case of a large industrial building, all the roof points can be filtered out, when the representative filter value is over the filtering threshold. When the 70% quantil is the representative filter value than at least 30% of the points must have such a large residual to the surface that it would be eliminated, in case this residual would be the representative filter value. In sample 22, it can be seen that the large roof in the bottom right corner is divided into more segments. Therefore, the segment in the middle has too small residual, which cause the type II error. The advantage of using segments is that these errors can be corrected easily, since all the points belong to this segment can be removed together. This advantage is profitable, if the segments are homogeneous, i.e. they contain points from only one type of object. An investigation has been carried out, where the homogeneity of the segments are presented with numerical values. For each segment a classification rate has been determined, which shows, how many percent of the points belongs to the same object type. Thus, in case, 93% of the segment's points are on the terrain and the segment is classified also as terrain than the remaining 7% belongs to type II errors.
All segments are classified into 3 groups according to these classification rates. Segments over a 98% classification rate are considered as 'correctly segmented', between 90% and 98% are considered as 'acceptable' and the rest are 'mis-segmented'. The results of sample 54 can be seen in table 7.16.

Segmentation classing	Rate of homogeneity	Rate of segments
'Correct'	$x \geq 98\%$	63,9%
'Acceptable'	$98\% > x \geq 90\%$	15,6%
'Mis-segmented'	$90\% > x$	20,5%

Table 7.16: Homogeneity of segments in sample 54

It shows that nearly 80% of the segments are 'correctly' or 'acceptably' segmented and 20% of segments contain a significant proportion of mis-segmented points. These results show that the segmentation should be further developed. The plane model of segmentation can not represent the run of terrain surface. In order to accept a bit of the terrain curvature, points are added to the segment within an approximately 30 cm threshold over the adjusting plane. It follows that outliers under this threshold can not be separated. This threshold can not be decreased to 0 using any kind of model, however there is still potential to approximate better the terrain surface and separate more outliers. A potentially more effective segmentation method would consider the curvature of the surface as well. So could terrain segments growing larger and possibly separating lower outliers as well. This segmentation method could be based on the analysis of terrain curvatures instead of plane adjustment, which could follow better the run of terrain.

7.1.4 Raster and TIN comparison

As it was mentioned in chapter 2.4.1, the chosen data structure influences the data processing as well. Theoretically, both methods have advantages and drawbacks, but which one performs better in practice? One test site has been investigated to compare the segmentation and filtering results in the case of TIN and raster data structure. Sample 22 has been chosen, because here vertically the overlapping stripes do not correspond perfectly to each other. It follows that the segmentation divides this overlapping area into many parts, even if there is a plane surface in reality. This error of segmentation affects the filtering results as well. The results of segmentation can be seen in figure 7.16. On the left, the segmented point cloud, while on the right, the segmented raster data are presented. The overlapping strips in the TIN model can be easily recognised, since all the segments are split up at the border of the overlapping areas. This shows the drawback of using point cloud in the segmentation process.

The point cloud has been interpolated to a 1m raster. Since point distribution is steady in raster format, a smaller neighbourhood (N8) is considered in the segmentation process. It can be seen that the resulted segments are not influenced by the strip adjustment error (figure 7.16). In consequence, the filter results seem to be better and the number of both type of errors decreases. A part of type II errors is caused by the rasterization, which can be noticed around the filtered objects. A visual comparison can be seen in figure 7.17 and the numerical evaluation in table 7.17.

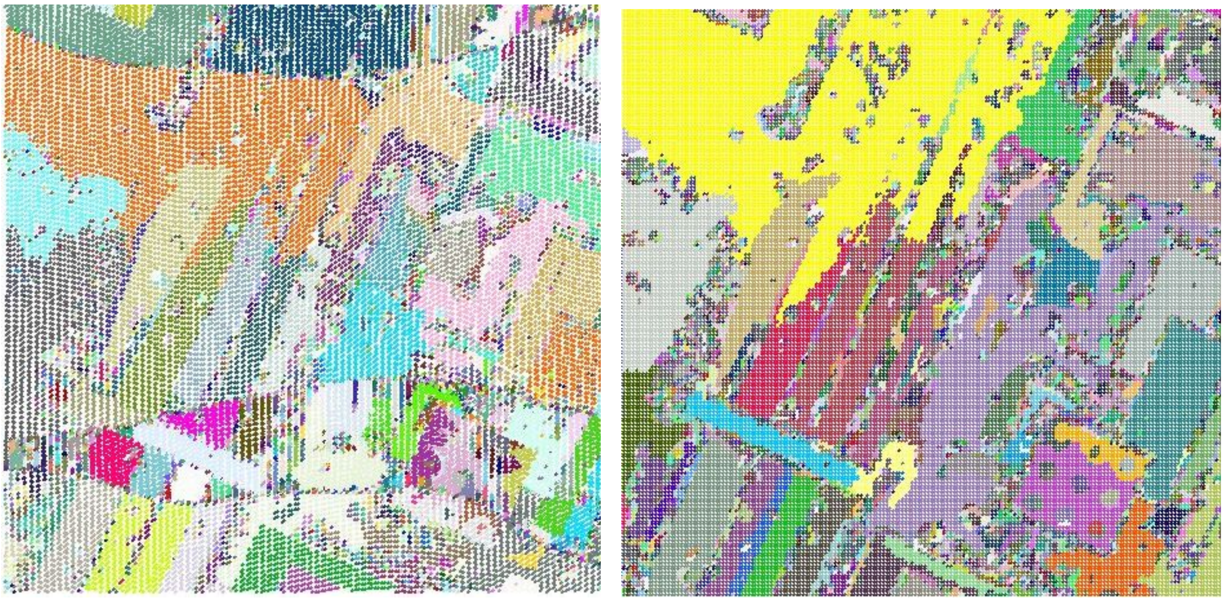


Figure 7.16: Segmentation results of TIN and raster- Sample 22

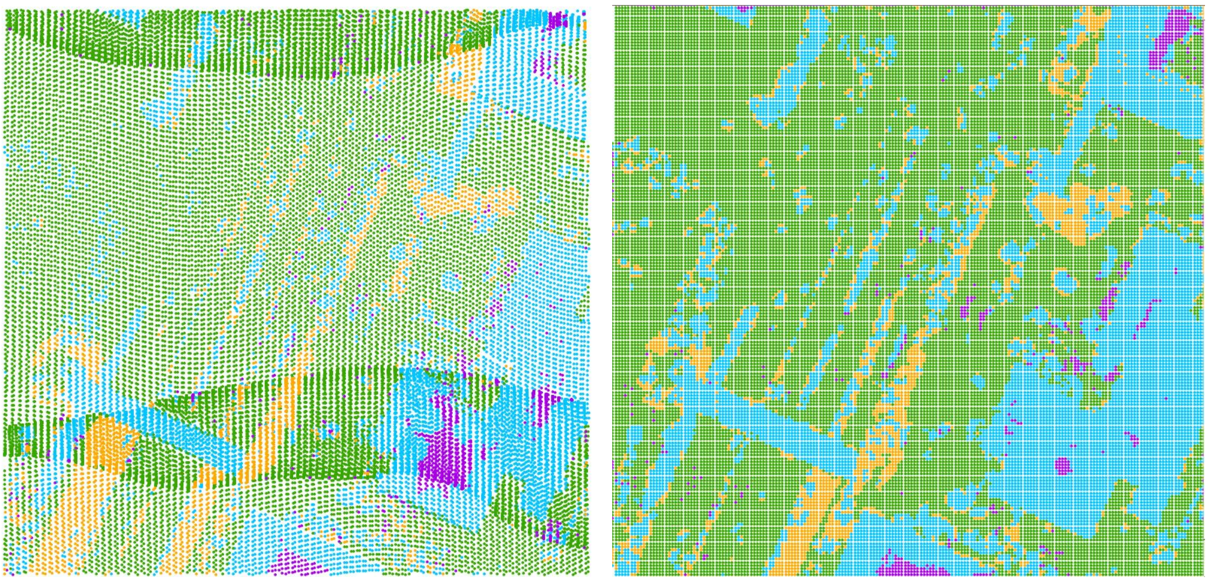
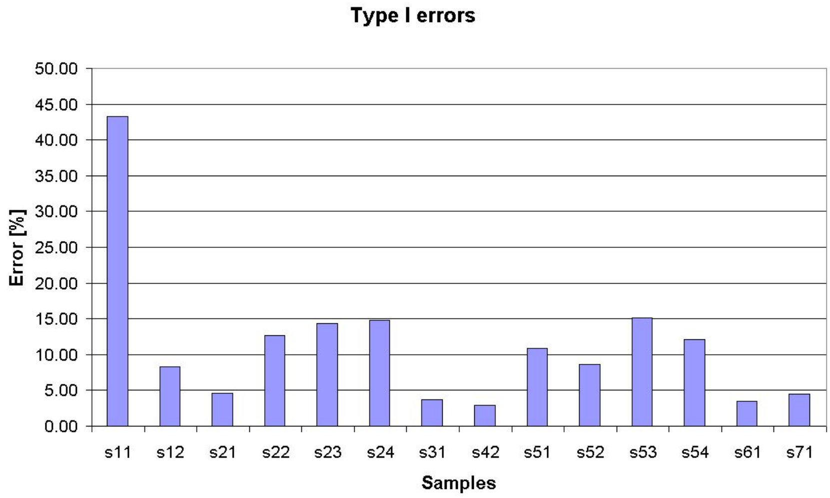


Figure 7.17: Filtering results of TIN and raster- Sample 22

		Filter result					
		Terrain	Object				
Reference	Terrain	**20234**	2871	23105	68.73%	**Type I**	**14.19%**
	Object	584	**9926**	10510	31.27%	**Type II**	**5.88%**
		20818	12797	33615		**Total**	**10.28%**
		61.93%	38.07%			**Ov. acc.**	**89.72%**

Table 7.17: Sample22 raster



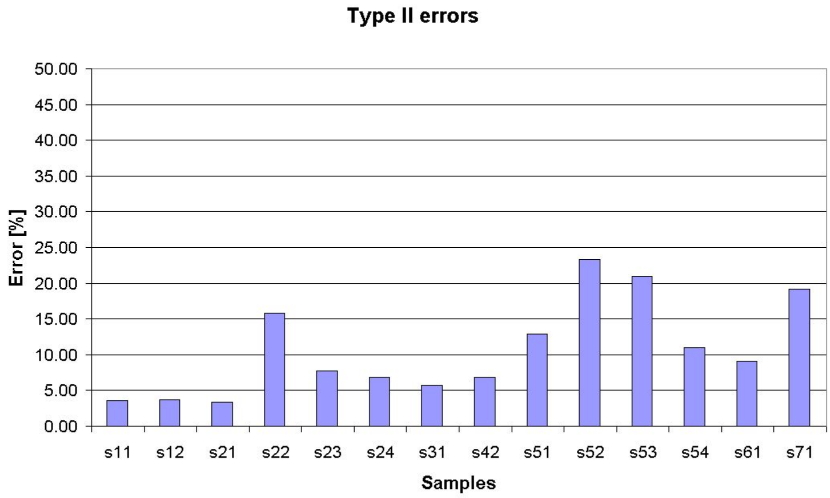


Figure 7.18: Type I and II errors

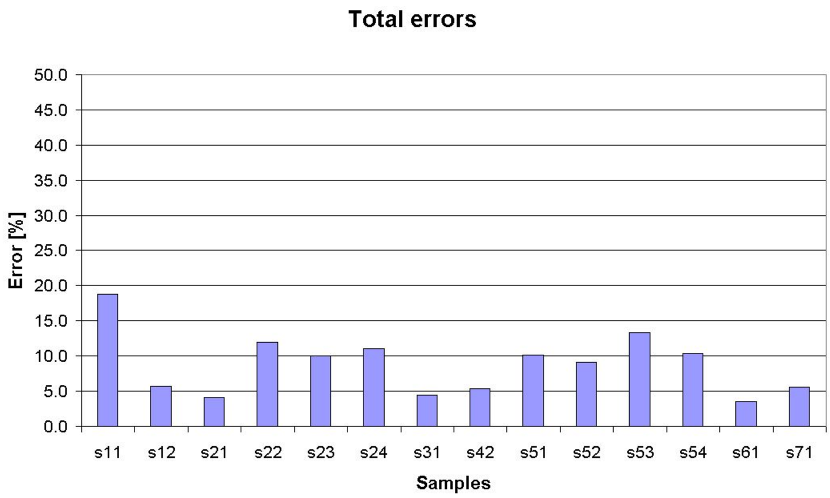


Figure 7.19: Total errors

7.1.5 Discussion

The performance of the segmentation based robust interpolation is not superior to the best existing filters, which are presented in the ISPRS filter test. A comparison with the point based robust interpolation by Pfeifer and Briese is very interesting. Since this approach works basically in a very similar way, the results show the differences between a point based and segment based filter performance. A numerical comparison of filter results does not show significant improvement or deterioration and the visual inspection show that the filtering errors occur typically on the same locations. In consequence of the segmentation, outliers can influence the filtering of the points in their environment. Depending on the topography, segmentation can influence advantageously and disadvantageously the filtering. Better results arise with the segment based approach, when the majority of the points in a segment would be filtered correctly also with the point based method. A considerable advantage is that errors may be corrected more simply, because point groups can be edited instead of single points. Since this method can not consider the proximity of the neighbouring segments, small segments near step edges may be classified incorrectly.
Results could be improved by another segmentation method, which considers the terrain characteristics better. This method does not use all type of information sources that are presented in chapter 4.2, therefore, the results are also limited in terms of precision. Using an explicit surface model in a segment filtering method gives a formerly not applied information source, whose reliability enables us to use it in a more complex filtering method that consider more information sources.
Using raster structure instead of TIN has increased the quality of the segment filtering method. Although the overall classification rate has become better, some details have been lost according to the rasterization.

7.2 Object classification

7.2.1 'Salem' dataset

This test site is located near Lake Constance. The data was captured by the TopoSys Falcon II sensor in the springtime of 2002 with an average point density of approximately $5\,points/m^2$. It was captured without the swing modus; therefore, the point distribution is a bit unfavorable. The very high point density on the other hand provides detail in abundance about the surface.
This rural hilly area contains settlements, forests, vineyards and overhead power lines. The vegetation consists of deciduous and conifer trees as well as bushes. First and last pulse echoes were captured and additionally last pulse intensity data were recorded.
The original point cloud has been interpolated to a $1\,m$ raster. As reference data, black and white orthophotos were used.
The relative small houses are surrounded by low and high vegetation. Some buildings are located on a slope. For the evaluation of results, greyscale orthophotos and topographical

maps have been used. These materials and the laser data have been captured and produced on different dates, there is 4 years difference in time. Unfortunately, they could not provide suitable information for a human operator in all cases with regard to an unambiguous classification of some points and objects.
The last pulse measurements have been filtered by the filter method of von Hansen and Vögtle (1999). The first pulse DSM can be seen in figure 7.20. The object segmentation procedure detects the objects, which are higher than 200 cm and the height difference between neighbouring points within a segment is less than 160 cm. These parameters were chosen, because buildings are higher than 200 cm, but terrain parts in the nDSM are mostly below this threshold. 160 cm were chosen in order to segment all the building parts (inclusive chimneys), and to separate high trees from small houses. The result of the object segmentation can be seen in figure 7.21. As a consequence of the imperfections of the filtering, some terrain parts are also segmented. This data set was used in the investigation of the fuzzy logic based classification as well.

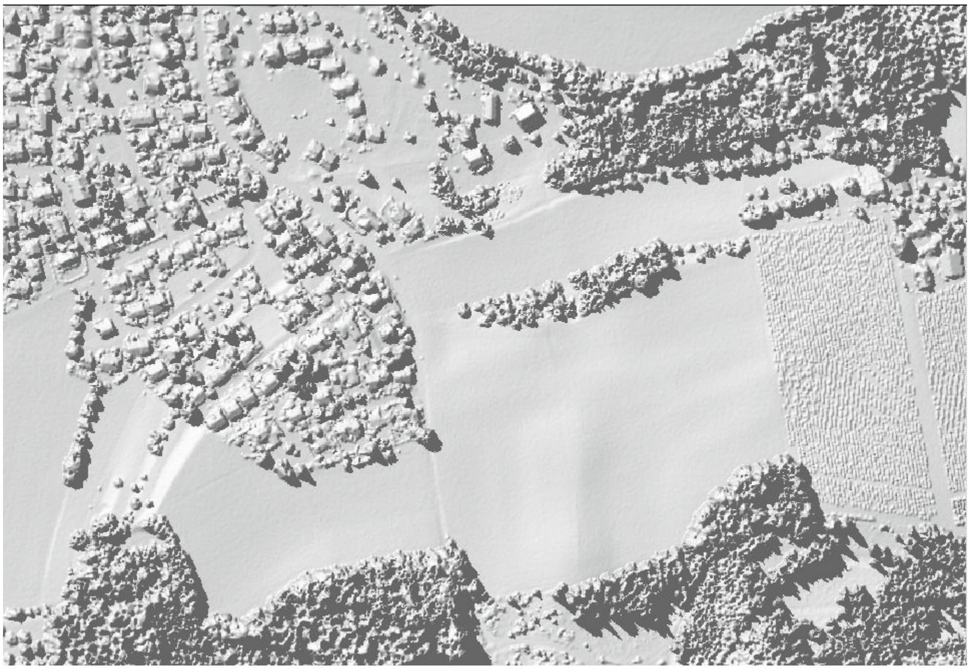


Figure 7.20: First pulse DSM of the 'Salem' dataset.

Object segmentation

The set of segmentable objects are well defined by the procedure parameters. Therefore, the not segmentable objects are not considered as errors. Errors are the over- and the undersegmented objects. Especially, undersegmentation can confuse the classification process, thus the parameters are chosen in order to avoid this error. Because of the high point density, the laser hits relatively often chimneys and antennas on the roofs. These objects should be part of the roof segment, therefore, a relatively big threshold (160 cm)

Figure 7.21: Segmented objects of the 'Salem' dataset.

has been chosen for the acceptable height difference between the neighbouring points. The lowest detectable height has been set to 2,00 m.
The segmented objects of the dataset can be seen in figure 7.21. The resulted segments are slightly undersegmented, some attached houses are connected together. Some densely vegetated areas constitute also segments, and some terrain parts are also segmented. The building segments are usually correctly segmented, errors can occur because of complex roof structures or by chimneys.

Object classification

The data characteristic enables us to extract the following object features for the classification:

- border gradients
- standard deviation of the point heights
- first and last pulse height difference
- height texture by the Laplace operator
- last pulse intensities
- shape parameters

The high point density enables to compute standard deviation within one raster element, hereby the feature values are centered on only one raster, the measurements have no influence in the neighbouring rasters. The first and last pulse differences are calculated as the highest difference within a raster, since first and last echoes were separately recorded, therefore, pulses belonging together can not be identified. Orthogonality and parallelism of the 4 longest sides have been used as shape parameter, which has been weighted by the area of the segment. However, the last pulse intensities are very noisy, nevertheless this feature could lead to a certain improvement of the classification quality. In this dataset, various feature combinations have been tested, which can be seen in table 6.4. The segmented objects have been classified into three classes: buildings; dense vegetation; and terrain. The terrain segments are usually extracted at places, where the run of terrain changes suddenly. In these segments, the rest of vegetation may partially remain. In the fuzzy classification process, four kinds of inference operators have been tested, and the product operator has been chosen for the final process (compare chapter 6.5). Maximum likelihood classification has been implemented as well in order to evaluate the fuzzy classification results (table 6.6).

The final results of object classification and vegetation detection can be seen in figure 7.22. The shaded relief is colored according to the object class. Vegetation class is green, buildings are red and segments are blue that are classified as terrain parts. Misclassification occurs between the building and terrain object classes in some cases, vegetation objects are detected with a high reliability. The misclassified segments are small while larger objects can be classified with a higher reliability.

In case, the classing is ambiguous, i.e. the entity may be classified with almost the same probability into more classes, the entity can be indicated as uncertain.

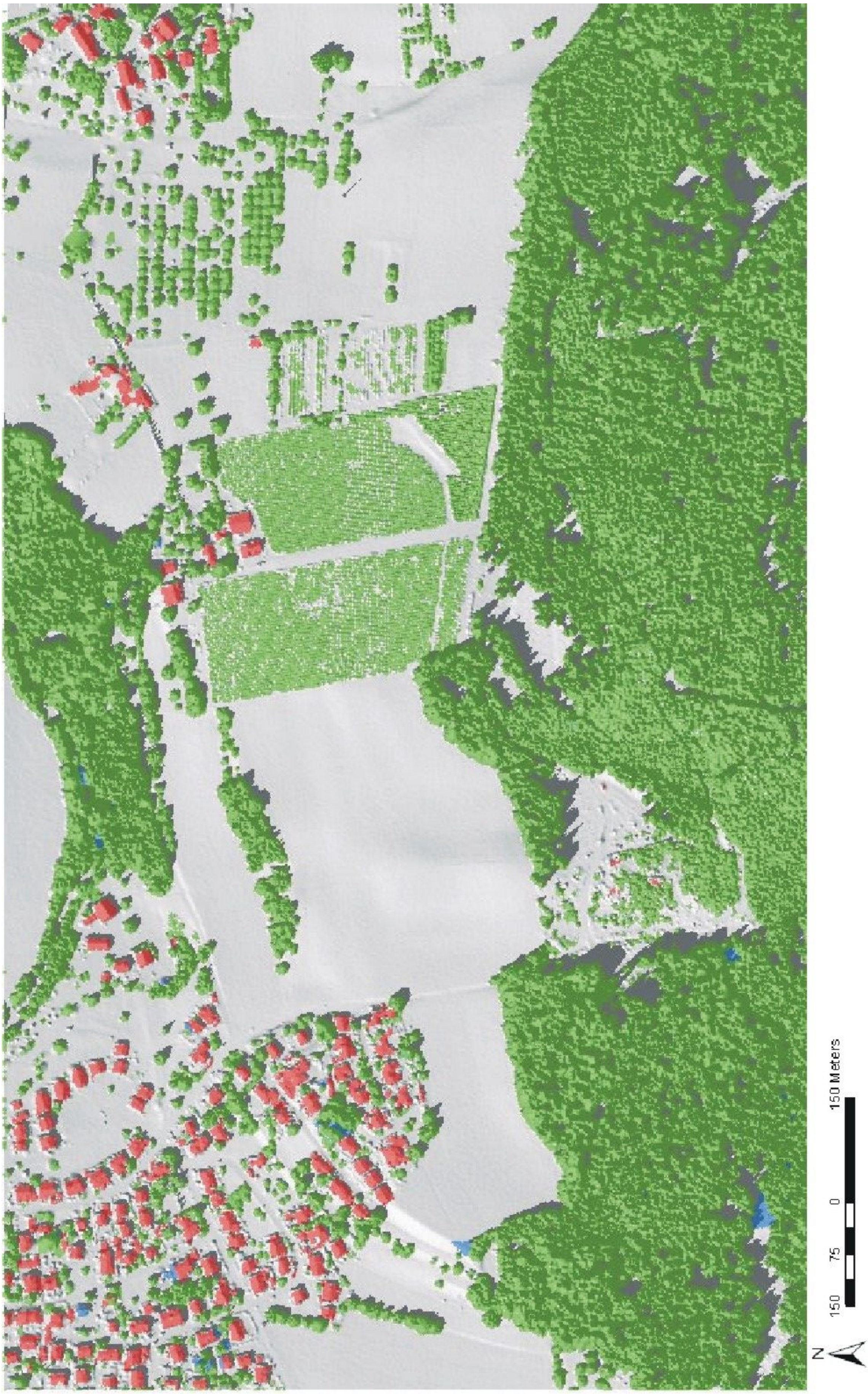


Figure 7.22: Classification result of 'Salem' test site. (Red - buildings, green - vegetation, blue - terrain objects and gray - terrain)

7.2.2 ISPRS dataset

The sufficient object classification results of 'Salem' dataset inspired us to test the method with a completely different dataset. The very high point density ($5\,points/m^2$) of 'Salem' dataset enables a relative reliable object detection and classification, therefore, a dataset with lower point density has been chosen. A lower point density can affect disadvantageously the object segmentation, feature extraction and classification as well.
A sample is selected from the ISPRS dataset in the Stuttgart area, which is also used for the segment based robust interpolation test.

Filtering

As this test area was already filtered by the segment based robust interpolation in the filter evaluation process, for the object generation the same terrain model has been used. The gross errors have been omitted manually, which are usually caused by the border effect, -i.e. near to the site borders. Otherwise the filter would not be able to eliminate the larger objects at the site borders.

Object segmentation

The lower point density causes a relatively smooth surface of last pulse nDSM. Last pulse echoes are backscattered with lower probability by outliers, like chimneys, therefore roofs are also represented as smoother surfaces in this dataset. The parameters of object segmentation are fitted to this characteristic, i.e. the acepted relative height difference of the neighbouring points is relatively small (80 cm) in order to prevent the connection of different types of objects. It can be avoided by the other parameter that smaller objects than 2,20 m are segmented. This condition excludes normal objects like cars, but enables us to detect the smallest buildings of the acceptable minimal size as well.
The examination of results of the object segmentation show that detached houses consist of one segment, while buildings with more height levels are divided into more segments. 6 small buildings are not detected and there are some complex buildings where some small parts are not segmented. The number of undetected buildings can be decreased by a higher acceptable neighbouring point height difference parameter. It would also cause more undersegmented buildings, which phenomenon is disadvantageous in the classification process. There are also some faulty segments, which do not represent a whole building. They are either only partially segmented, which can be caused by the minimum height condition, or some other objects are connected to the segment, which can happen when there is smooth transition between the objects (e.g. truck close to a small building).

Object classification

The acquired data enable us to extract the following features for each 3D object:

- border gradients
- standard deviation of the point heights
- first and last echo differences
- geometry of the 4 longest side
- first pulse intensities
- area

According to the different data characteristics, the values of the extracted features differ slightly as well. Therefore, the membership functions are adjusted to these values. Here first and last pulse differences are not computed on the bases of spatial relations, but the original measurements are connected one by one to each other, therefore, the real height differences are used. The mostly point density dependent feature is the root mean square errors of the heights, since $0.67\,points/m^2$ does not enable us to compute it within a 1m raster. Therefore, it can be computed only taking into account the neighbouring pixels. First pulse intensity values could not improve the classification reliability, therefore, this feature is not used in the final classification.

Building segments are well detectable from these features. The rest of the segments are part of the ground, which are segmented due to the imperfect terrain extraction. Normally, these elements are usually mixed with other types of objects, like vegetation, cars or fences, therefore, they are not classified further. Lower vegetation is also hardly distinguishable from other small objects, thus trees are the main objects of the vegetation detection.

Classification results can be seen in figure 7.23. On the shaded relief, buildings are indicated by red, vegetation is colored green, misclassified segments that are not buildings are drawn in blue, and segments that are misclassified as vegetation are indicated by yellow. Segments that are misclassified as buildings are usually limited partially by vertical walls, they have relative smooth surfaces and are not covered by vegetation. These objects are usually man-made as well.

Vegetation detection is based on the first/last pulse differences. The misclassified points are usually at the border of high buildings or walls as well as at extended roof tiles made from transparent material. The rate of these misclassifications is tiny. The undetected trees have small crowns, which might be eliminated by a morphological filter in the process, where man-made objects that generate high first and last pulse differences (e.g. street lamps) are excluded.

The almost 90% classification rate of buildings and vegetation shows that the object segmentation and classification process can be used with lower density data as well, without a significant quality deterioration. Naturally, a higher point density enables a more reliable feature extraction and a more sophisticated object classification.

7.2.3 Discussion

The great advantage of this object classification method is that it offers a general approach. All parts of the process can be substituted by another similar method. Two different types of filters have been tested for the nDSM generation and the quality of the filtering did not make much difference in the resulted nDSM. However, only one object segmentation method has been used over all test sites, but because of the relatively simple method, most probably other algorithms could segment the detached objects as well. Different classification methods have been also tested. Fuzzy logic and maximum-likelihood methods resulted in similar classification rates. Fuzzy logic offers a relatively wide scale of solutions for this task.

The errors of object classification may be caused by:

- segmentation errors
- insufficient quality of features
- imprecise determination of class features in fuzzy classification
- insufficient quality of data

The segmentation errors are caused by different objects that are located very close to each other and there is a relative smooth surface transition between them. This can happen e.g. between a smaller house and a tree of similar height or between a small house and a truck. This undersegmentation failure may cause that feature values for this segment are calculated over these different types of objects. Therefore, on the basis of these feature values, an unambiguous classification is not possible. The oversegmentation of objects may cause that features are extracted only from a few measurements. Since the classification of small segments is not as reliable as those of large segments, oversegmentation should be avoided as well.

An important part of the classification is the determination of suitable and extractable features. Since there is a huge variety of data characteristic, depending on the scanner type and point density, a general solution for the best feature combination is not possible. First and last pulse height differences and height texture features - especially standard deviation of heights within a raster - can mostly improve the quality of results. Geometrical parameters work well in the case of larger segments, and intensities can be utilized with variable success. Using exclusively first or last pulse data, the success of object classification is doubtful. Nowadays, airborne laser scanners can record at least two pulses, therefore, they can provide sufficient information for this approach.

The results are influenced by the definition of membership functions in the fuzzy classification as well. In cases where the overlap between the feature values of different classes is relatively large, the membership functions of the classes should be determined more precisely.

Places, where errors appear in the results are usually 'special cases'. These may not be solved completely by better algorithms, only by using more adequate quality of data.

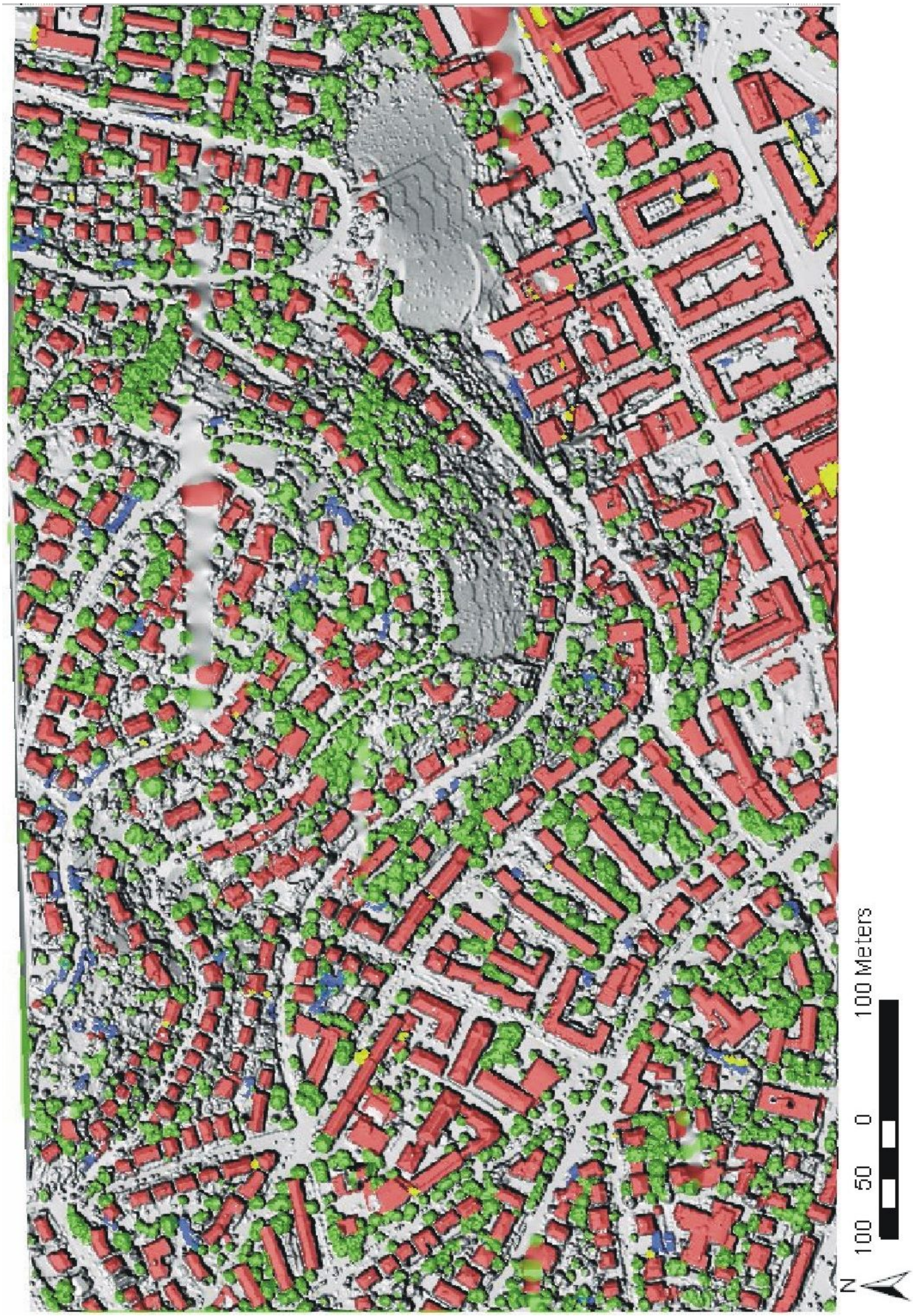


Figure 7.23: Classification result 'Stuttgart' test site. (Red - buildings, green - vegetation, yellow - misclassified vegetation, blue - misclassified buildings)

Chapter 8

Conclusions and perspectives

In this thesis a strategy has been presented which is able to classify terrain points, as well as building objects and vegetation. The presented results show that ALS data is suitable for extraction of this information. However, this ability is limited in terms of the number and kind of object classes; but the main object types can be separated.

The advantage of this approach is that it works not only as a particular method, by using special algorithms, but it offers a general solution for this task, so other filtering, segmentation and classification methods can be applied as well.

The task of filtering can be implemented with the best results, when as much knowledge as possible are taken into account about the terrain and object characteristics. The classification of points either to the terrain class or to the object class is based on the features of the processing elements -taking into account the knowledge about these classes. If the processing element (point or segment) is the smallest entity - i.e. a point - than the extractable features are limited to its geometrical, radiometrical values and to its neighbourhood relations. In case the entity is a group of adjacent points then this local region offers more additional features. The difficulty of this classification is to extract the most features of the objects from single discrete measurements.
Filters are usually based on simple assumptions that more or less correspond to reality. Due to these simple assumptions, they usually apply only one or two information sources for the filtering. From these few pieces of information only a part of the possible extractable features can be extracted. Using more information sources, more features can be extracted and more complex assumptions can be made about the terrain surface. To process more information, a more complex method is needed, which is able to weight and fuse the individual pieces of information. This classification based filter could be implemented by a fuzzy method, because it can handle ambiguous and controversial information.

Segmentation based robust interpolation applies a new kind of information source, while it considers the distance between the segments and the approximated terrain surface. Since this method does not use all sources of information, the results are also not better than the results of other filters. The segment based robust interpolation approach shows a new source of information what could be used in a more sophisticated procedure: that uses the most possible sources of information.

The segmentation method that has been used for terrain segmentation is originally designed for terrestrial laser data in order to extract approximately plane surfaces. Since this assumption is only valid locally in the case of terrain, the segments can not follow the run of terrain. Another method is needed which can consider better the terrain characteristic. This could be e.g. a method which is based on the curvature of the surfaces.

Segmentation of terrain points for terrain filtering and segmentation of objects for object classification are solved in two different steps. Both segmentation methods work on one simple assumption each. For the filtering, surface segments are determined that can be approximated by a plane. With this condition a rough approximation of the real terrain surface can be made. This condition can not work in object segmentation, since the surfaces of these objects are more complex. A complex surface of a building or vegetation can be detected if it is assumed that its surface is higher than the terrain surface and neighbouring points on the object surface are not far from each other. However, these two assumptions - i.e. the two different segmentation approaches - are quite different, they could cooperate within the same process. Of course, it is also required that the classification works within this process as well, since terrain and object points should be separated.

The classification of objects is more reliable if the extension of the object is relatively large. Very small and especially very low objects that are acquired only with a few measurements are hardly classifiable. These objects could be classified only when more precise measurements with higher point density would be available. The quality of segmentation influences the classification results. More types of objects merged in the same segment confuses the classification and the result becomes unreliable.

Filtering, object segmentation and classification are well separated procedures in this approach.
The segmentation of terrain or objects is based on some geometrical assumptions on the objects. These assumptions can be considered as classification conditions. The more precise segmentation is needed, the more conditions are necessary in the segmentation process. Since segmentation is a precondition of classification - and here also vice versa - the two procedures will become no more separated, i.e. they will be one procedure together. Filtering is also a kind of supervised classification in this case and it may be integrated also in the same process.

The approach is implemented partially only on raster bases. The whole method should be able to work in the future completely on TIN data as well.

New sensors, that can digitize the full waveform, or that can measure with more wavelengths may provide much more suitable data for classification of high and low objects in the future. Laser scanners are still for greater development steps and of course this needs more sophisticated data processing as well.

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