Detection and Recognition of Objects from Mobile Laser Scanning Point Clouds

Case studies in a road environment and power line corridor

Matti Lehtomäki
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Abstract

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Abstract
Accurate and detailed three-dimensional (3D) geospatial data are needed, and they open new future possibilities. The collection and processing of data should be efficient to add value for society. Mobile laser scanning (MLS) is a detailed 3D mapping technique that can produce 3D point cloud data with a sub-centimetre relative accuracy. Data collection is efficient, and in a road environment, hundreds of kilometres can be mapped daily. MLS produces large amounts of data (eg 1 gigabyte per 1 km of road), and the processing should be automated for the technique to be practical and efficient.

This thesis studies the automated interpretation of the 3D point clouds collected using MLS. First, it investigates how completely and correctly polelike objects, such as traffic signs and lampposts, can be detected from MLS point clouds in a road environment. Second, it studies if the accuracy of general object recognition from MLS point clouds can be improved using new algorithms. Third, the detection of power line components is studied outside the road network, both in forests and on farmland. Object detection and recognition algorithms are developed and tested with real-world data collected in a road environment and a power line corridor outside the road network. The algorithms’ accuracies are evaluated quantitatively.

The results suggest that polelike objects can be detected with an accuracy of between 70% and 87% in a suburban environment. These results are among the first to evaluate the accuracy of polelike object detection quantitatively, implying slightly higher accuracies than previous studies. For the first time, local descriptor histograms (LDHs) are applied to machine-learning-based object recognition from MLS point clouds in surveying applications. The results suggest that LDHs can increase the accuracy of the point cloud segment classification – a 9.6 percentage point increase is observed compared to a state-of-the-art accuracy of 78.3%. Undersegmentation and incomplete ground extraction are the most prominent error sources in object recognition. MLS is applied for the first time in power line detection outside the road network, in forests and on farmland. The results imply that the accuracy of automated power line detection may be higher than 93%. Most errors are caused by the inaccuracy of the trajectory and attitude determination, probably due to tall trees blocking navigation satellite signals.

This dissertation demonstrates the potential of MLS in the automated mapping of the road environment and the power line corridor outside the road network. The thesis also presents techniques that may improve the accuracy of the automated data interpretation. In addition, the dissertation points out some limitations of MLS technology through error analyses, providing directions for future research.

Keywords
mobile laser scanning, point cloud, algorithm, automated interpretation, detection, recognition, classification, feature extraction, road, power line

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Tarkalle ja yksityiskohtaiselle kolmiulotteiselle paikkatiedolle on tarvetta ja se avaa uusia mahdollisuuksia. Aineiston keräämisen ja käsittelyn tulisi olla tehokasta, jotta se tuottaisi lisäarvoa yhteiskunnalle. Liikkuvaa laserkeilaus (LL) on yksityiskohtainen kolmiulotteinen kartoitustekniikka, joka tuottaa pisteipilvaineistoa, jonka suhteellinen tarkkuus on millimetritolukossa. Datankeruu on tehokasta – päivissä voidaan kartoittaa satoja kilometrejä. Liikkuvaa laserkeilaus tuottaa suuria määräa dataa (esim. 1 Gt kilometriä kohden), jonka käsittely tulisi automatisoida, jotta tekniikka olisi käytännöllistä ja tehokasta.


Väitöskirja havainnollistaa, kuinka liikkuvaa laserkeilausta voi soveltaa tiempäristön ja tieverkon ulkopuolisen sähkölinjakäytävän automaattisessa kartoitukseksessa. Työssä esitetään myös teknikoita, jotka voivat tarkentaa pisteipilvaineiston automaattista tulkintaa. Virheanalyysien avulla väitöskirja tuo esiin joitain LL:n tekniikan rajoituksia osoittaa näin lisätutkimuksen

**Avainsanat** liikkuvaa laserkeilaus, pisteipilvi, algoritmi, automaattinen tulkinta, havaitseminen, tunnistus, luokittelu, piirreerrotus, tie, sähkölinja

**Tekijä** Matti Lehtomäki

**Väitöskirjan nimi**

Kohteitten automaattinen havaitseminen ja tunnistaminen liikkuvalla laserkeilaaimella kerätyistä pisteipilvistä

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Preface

This thesis gathers the research carried out when I was working first at the Finnish Geodetic Institute and later at its successor, the Finnish Geospatial Research Institute, National Land Survey of Finland, both known as the FGI. The financial support of the Academy of Finland, Business Finland (previously Tekes, the Finnish Funding Agency for Technology and Innovation), the Aalto Energy Efficiency Research Programme, and the RYM Oy research programme ‘Energizing urban Ecosystems’ is acknowledged in several projects in which I have worked during the writing of the thesis. Although I use the personal pronoun ‘I’ in the text, because I am the only author, I wish to emphasise that all this dissertation’s publications are a product of collaborative research. I apologise for some stylistic mistakes in the beginning of the book, which give me the opportunity to improve my LaTeX skills in future.

First, I wish to express my gratitude to Prof. Juha Hyyppä, the Head of the Department of Remote Sensing and Photogrammetry. Thank you for your guidance and support, as well as your successful leadership of the department. Under your tutelage, I have learnt, among many other things, much about science and have become a better writer.

I also wish to express my gratitude to Dr Anttoni Jaakkola, Prof. Antero Kukko, and Prof. Harri Kaartinen for their support and guidance. Thank you also for designing and building the various mobile mapping systems – with Prof. Hyyppä inspiring you – and using them to collect the datasets that made this thesis possible. I wish to thank Dr Jaakkola for the inspiration and help in the algorithm development.

I am also grateful to Prof. Jouko Lampinen for his supervision, which already started during my master’s phase. Thank you for your guidance and support. I have enjoyed our fruitful, inspiring, and encouraging discussions, and I have learnt a lot from you.

I wish to thank Prof. Jonathan Li and Prof. Cheng Wang for pre-examining the manuscript of the dissertation and for their reassuring comments.

I am also thankful to all the other co-authors of the papers included in this thesis, namely, Dr Leena Matikainen, Dr Eetu Puttonen, Dr Xiaowei Yu, Prof. Yi Lin, and Prof. Hannu Hyyppä. Your contributions are highly appreciated. I
also wish to thank everyone with whom I have collaborated over the years.

I am grateful to the Director Generals Prof. Risto Kuittinen and Prof. Jarkko Koskinen, and Research Director Prof. Tiina Sarjakoski, for enabling FGI to be a safe and inspiring working environment and an esteemed international research institute.

I wish to thank everyone at FGI and in Masala for creating an enjoyable working environment. Sport activities, coffee breaks, fieldwork trips, and summer trips – to name only some – have given me strength to continue with the research. The FGI and the National Land Survey of Finland are acknowledged for various support and services, including IT, library, cleaning, communication, and well-being at work, as well as interesting and rewarding training. I would also like to acknowledge the help and support I have received from the shop stewards.

I also wish to thank Arto Kuskelin from the Finnish infrastructure and construction service company Destia for providing information on the road defect inventory, and related costs and prospects in Finland, and Dr Carlos Cabo for providing details about his research. The Aalto University’s Language Centre deserves a special thank for the support I received while preparing the Lectio Praeursoria, which was a most fruitful and rewarding process. I hope that the students of Aalto University find the valuable resources the centre provides.

Finally, I wish to express my gratitude to my family, friends, and relatives for your support over the years. I especially wish to thank Jaakko and Juho for friendship, support, and collaborative learning, and my sister Taru and brother Vesa for all their support and encouragement.

Espoo, July 14, 2021,

Matti Lehtomäki
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This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.


Author’s Contribution

Publication I: ‘Detection of vertical pole-like objects in a road environment using vehicle-based laser scanning data’

Lehtomäki had the main responsibility for developing and implementing the algorithms, the experimental design related to data analysis, performing the data analysis experiments, and manuscript preparation. Jaakkola and Hyyppä contributed to the initiation of the research questions. Jaakkola contributed to the algorithm development in discussions. Hyyppä contributed to the design of experiments and to the writing of the manuscript. Kaartinen and Lehtomäki collected the field reference, and Lehtomäki the data reference. Kukko and Kaartinen were responsible for the design and building of the mobile mapping system, and Kukko, Kaartinen, and Jaakkola designed the data collection campaign and collected, georeferenced, and preprocessed the data. The co-authors revised the manuscript and made suggestions for improving it.

Publication II: ‘A low-cost multi-sensoral mobile mapping system and its feasibility for tree measurements’

Jaakkola was responsible for the design and building of the mobile mapping system, collecting the data, proposing the idea of a multi-sensor multi-platform low-cost system, the design of the case studies, and writing the general parts of the article and the system description. Hyyppä contributed to the planning of the case studies and the low-cost systems, especially to the planning of the mini-UAV concept, and to the writing of the article. Case studies were dealt with by Jaakkola and the co-authors. Lehtomäki had the main responsibility in the pole and tree trunk detection case study from car-based laser data (first paragraph of Section 4.1. and Figure 8 in the article). There, he developed and implemented the algorithms, collected the reference from the point cloud, designed the data analysis experiments, performed the data analysis experiments, and wrote the
paragraph in the article, which was revised by the co-authors.

Publication III: ‘Performance analysis of a pole and tree trunk detection method for mobile laser scanning data’

Lehtomäki had the main responsibility for the experimental design related to data analysis, collecting the references from the mobile laser scanning (MLS) and static terrestrial laser scanning (TLS) point clouds, performing the data analysis experiments, and manuscript preparation. Kukko and Kaartinen were responsible for the design and building of the mobile mapping system, and Kukko, Kaartinen, and Jaakkola designed the data collection campaigns and collected, georeferenced, and preprocessed the MLS and TLS data. The co-authors revised the manuscript and made suggestions for improving it.

Publication IV: ‘Object classification and recognition from mobile laser scanning point clouds in a road environment’

Lehtomäki had the main responsibility for algorithm development and implementation, the experimental design related to data analysis, collecting the reference from the point clouds, performing the data analysis experiments, and manuscript preparation. Jaakkola, J. Hyppä, and Lampinen contributed to the research question initiation, and Jaakkola and Lampinen to the methodological developments in discussions. J. Hyppä participated in writing the manuscript. Puttonen contributed to the data processing. Kukko and Kaartinen were responsible for the design and building of the mobile mapping system, and they designed the data collection campaign and collected, georeferenced, and preprocessed the data. J. Hyppä and H. Hyppä contributed to the research planning. The co-authors revised the manuscript and made suggestions for improving it.

Publication V: ‘Power line mapping technique using all-terrain mobile laser scanning’

Lehtomäki had the main responsibility for developing and implementing the algorithms, the experimental design related to data analysis, collecting the reference from the point clouds, performing the data analysis experiments, and manuscript preparation. Kukko, Hyppä, Kaartinen, and Jaakkola contributed to the initiation of the research questions. Kukko contributed to the design of data analysis experiments and method development in discussions. Kukko, Matikainen, and Hyppä participated in writing the manuscript. Kukko and Kaartinen were responsible for the design and building of the mobile mapping
systems, and they designed the data collection campaign and collected, georeferenced, and preprocessed the data. The co-authors revised the manuscript and made suggestions for improving it.
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Abbreviations

**ALS**  airborne laser scanning

**ATV**  all-terrain vehicle

**CC**  connected component

**CPLS**  connected power line search

**ETRS**  European Terrestrial Reference System

**FGI**  Finnish Geospatial Research Institute (former Finnish Geodetic Institute)

**GNSS**  global navigation satellite system

**GPS**  Global positioning system

**HD**  high definition

**IMU**  inertial measurement unit

**LDH**  local descriptor histogram

**lidar**  light detection and ranging

**MLS**  mobile laser scanning

**PCA**  principal component analysis

**PLS**  personal laser scanning

**PMR**  point measurement rate

**PRR**  pulse repetition rate

**RANSAC**  random sample consensus

**SLAM**  simultaneous localisation and mapping

**SVM**  support vector machine
Abbreviations

**TLS** terrestrial laser scanning

**UAV** unmanned aerial vehicle

**WGS 84** World Geodetic System 1984
Symbols

\( n_{\text{ref}} \) the number of all reference targets

\( n_{\text{TP}} \) the number of detected reference objects by an algorithm

\( n_{\text{FP}} \) the number of commission errors
1. Introduction

1.1 Background and motivation

Geospatial data and products derived from them as, for example, maps are crucial to the functioning of a modern society. Car and personal navigation rely on maps, and topographic maps and digital elevation models are used in planning, zoning, hydrological modelling, mapping of flood risks, and forest inventories – to name only some examples.

Increasing the accuracy and level of detail of maps opens new possibilities to improve efficiency and safety, and to create new business and technology. For example, accurate and detailed maps of road environments improve safety by enabling the recognition of dangerous areas (e.g., poor visibility, or cracks and holes on the road surface). High-definition (HD) maps that contain detailed spatial information of the road environment (e.g., lanes, kerbstones, traffic infrastructure, vegetation, and buildings at a centimetre level) will strongly benefit – or even be vital to – autonomous vehicles [118], which will probably revolutionise society in coming decades.

Maps and other geospatial data products need to be produced efficiently in the competitive world. The mapping of overhead power lines, their components, and corridors in high detail enables the reliable monitoring of their condition, which, in turn, increases the reliability of electric power transmission and distribution. If this could be done efficiently, it would translate into enormous global savings.

Mobile laser scanning (MLS) technology combines various mapping and navigation sensors to produce accurate and dense spatial information from the surrounding environment [102, 99]. The data are usually produced in the form of three-dimensional (3D) point clouds that consist of dense and accurate 3D measurements of object surfaces. MLS can be operated using various platforms, such as cars, boats, and personal backpacks, and in differing environments, as, for example, roads, streets, forests, and rivers [71, 85]. The MLS data capture objects in the mapped area with a high accuracy and level of detail. Typical point density is hundreds or thousands of points per square metre, and the accuracy
is at a centimetre and millimetre level, at a global and local scale, respectively [61]. MLS can also cover large areas quite efficiently: hundreds of kilometres of road can be mapped daily with an MLS system. MLS complements airborne laser scanning (ALS) and static terrestrial laser scanning (TLS). ALS is the most efficient technique in the mapping of large areas, whereas TLS provides the most detailed and accurate data. MLS produces higher point density and 3D accuracy than ALS, and MLS captures narrow vertical structures as, for example, lampposts, which are challenging for ALS [10]. MLS can cover larger areas than TLS. In some environments, MLS may be applied with less effort and more flexibly than ALS when the mapped area is not particularly large [71].

In a road environment, MLS is used to map and model objects such as traffic signs, lampposts, and trees [101, 40] that can be used in maintenance, inventory, and planning. Polelike objects such as lampposts and traffic signs could also be used as reference targets to improve the accuracy of the georeferencing of the MLS data. Accurate data also enables the production of virtual 3D models of the environment. MLS data cover the surrounding building walls [114] which may be utilised in map updating. Presumably, MLS will be a key technology in the production of HD maps for self-driving cars in future [118].

In a power line corridor, MLS produces detailed 3D data of the power line components and the surrounding environment for inspection purposes [94]. In future, airborne laser scanning – either using an unmanned aerial vehicle (UAV) or a manned aircraft – will probably be the most popular technique for inspecting the condition of power line corridors, especially outside the road network [94]. However, MLS could complement the inspection by filling the gaps that remain after an aerial campaign. In some situations, MLS alone may even be an economically feasible choice for the inspection. In addition, compared to ALS, more detailed modelling of the power line components and surrounding vegetation is possible due to the high point density and accuracy of the MLS data.

MLS produces huge amounts of data (e.g., 1 gigabyte per 1 km of road) and manual interpretation of the data is too slow and inefficient. Automated data interpretation methods are therefore needed to utilise the full potential of the technology. For example, automated data processing workflows are essential when making full use of the nationwide point clouds [130] (both airborne and mobile terrestrial), which have been proposed as the core of the future topographic data. Mobile laser scanning could also be used with luminance imaging to model the street environment lighting [128], and automated object extraction methods would enable the efficient analysis of large areas.

1.1.1 Terminology

The terms ‘object detection’ and ‘object recognition’ in the title of this thesis refer to the automated discovery and the following categorisation, respectively, of objects from point clouds by an algorithm. Object detection means we wish to
find some specific objects in the data – for example, all trees. Object recognition means that once we have detected an object, we wish to categorise it. I also use the term ‘mapping’ as a synonym for detection in the power line case study. The term ‘feature extraction’ is used in machine learning to refer to the extraction of a feature vector that is given as an input to a classifier, for example. The term ‘object extraction’ is also used throughout the thesis overview to denote the combined detection of an object and retrieval of points belonging to it. Unfortunately, in Publications I–V, the distinction between object detection and extraction was not always clear and the two terms were sometimes used interchangeably. All object detection algorithms developed in this thesis could also be called object extraction algorithms, because the algorithms also retrieve points belonging to the objects, and not only bounding box, for example. Segmentation is close to object extraction. However, segmentation does not aim to detect specific objects, but rather to divide the data – point cloud or image, for example – into homogeneous areas, regions, volumes, and surfaces, for example. Segmentation may also refer to the retrieval of points belonging to a detected object. I decided to use the term ‘object detection’ instead of ‘object extraction’ in the title and research questions of the thesis, because it was not assessed how completely and correctly points belonging to objects were retrieved, that is, segmentation accuracy was not evaluated.

The term ‘polelike object’ is used throughout the thesis to denote an object that has an elongated ‘polelike’ shape. Vertical polelike objects encountered in a road environment mainly comprise traffic signs, traffic lights, lampposts, flag poles, utility poles, and tree trunks. I use the term ‘reference’ to denote the ground truth, that is, the known object locations and classes, typically manually collected by a human operator.

1.2 Research questions

This dissertation deals with the automated interpretation of the data that the MLS technology produces. The thesis seeks to identify how accurately it is possible to detect and recognise objects from MLS points clouds, if it is possible to improve the accuracy of the current object recognition methods by applying new ones, and the quality of automated object detection and recognition. The objects to be detected and recognised are the ground, buildings, traffic signs, lampposts, and power lines, for example. The outputs of the algorithms, that is, the object locations and their classes, produce valuable information in applications such as inventory, planning, and inspection. The algorithms are also a prerequisite for an automated workflow for 3D modelling.

This thesis focuses on the application of MLS to two environments, namely a road environment and a power line corridor outside the road network. The road environment data interpretation is divided into two themes. The first theme focuses on the detection of vertical polelike objects (e.g., lampposts and traffic
The second theme deals with a general classification and recognition of several object classes in a road environment. The interpretation of the power line corridor data focuses on the detection of power lines (conductors) and power line poles in forested areas and on farmland, both outside the road network. In particular, the following three research questions are considered in this thesis:

1. How completely can polelike objects be detected from MLS point clouds in a road environment, and what is the quality of the results?

2. Is it possible to improve the accuracy of machine-learning-based object recognition from MLS point clouds in a road environment by using classification features that are based on the distribution of local descriptors, and what is the quality of the results?

3. How completely can power lines be detected from MLS point clouds outside the road network, and what is the quality of the results?

1.3 Objectives

The objectives of the thesis in relation to the research questions are listed below in this section.

Objectives related to the detection of polelike objects in a road environment

• To develop algorithms for the detection of polelike objects in a road environment

• To test the developed methods experimentally using real-world data, and to evaluate the accuracy of the algorithms quantitatively

Objectives related to object recognition in a road environment

• To answer research question 2, an automated object recognition workflow was developed in PIV that followed the basic principles reported in previous research; see, for example, [101, 40].

• The main objective was to compare different geometrical features that are used in the machine-learning methods that are used to classify point cloud segments.

• In particular, the objective was to identify if local descriptor histograms could
increase object recognition accuracy compared to state-of-the-art methods.

- The objective was also to test the whole object recognition workflow using real-world data, and to evaluate the workflow’s accuracy quantitatively to find the main error sources that may reduce the accuracy of the object recognition.

Objectives related to the detection of power lines outside the road network

- To develop algorithms for the detection of power lines from MLS point clouds outside the road network.

- To test the developed methods experimentally using real-world data, and to evaluate the accuracy of the algorithms quantitatively

1.4 Restrictions to the scope of the thesis

I focus on the recognition of whole objects from the point clouds, and I therefore do not discuss pointwise approaches, which have been studied in [96, 89], for example.

1.5 Contribution

The main contribution of the thesis is threefold. First, Publications I–III are among the first to study automated polelike object detection using mobile laser scanning, and reporting quantitative accuracy evaluations of the algorithms. The accuracies reported in PI and PIII – between 70% and 87% – were at least slightly higher than those reported in previous studies. The polelike object detection algorithms reported in PI and PII introduced the following novelties compared to previous algorithms: 1) the algorithms were able to separate polelike objects attached to each other; 2) the algorithms did not need training data as did previous machine-learning methods; 3) the algorithms utilised the sensor configuration of the MLS system to optimise the accuracy of the detection and to enhance computational efficiency.

Second, the thesis reports an application of advanced machine-learning techniques, namely, local descriptor histograms and spin images, to object recognition from MLS point clouds collected for surveying applications (IV). The results suggested that the machine-learning techniques could increase object classification accuracy from the state-of-the-art accuracy of 78.3% to 87.9%.

Third, the thesis demonstrates how all-terrain mobile laser scanning – using either personal backpack or an all-terrain vehicle – can be applied for the
Introduction

automated mapping of power line corridors outside the road network (V). The results suggested that by modifying the existing automated data processing algorithms developed for urban and road environments, power lines can be detected with an accuracy of higher than 93% in forests and on farmland.

Below, the contributions of Publications I–V are described in more detail.

**Publication I** reports a study of the automated detection of vertical polelike objects from mobile laser scanning data in a road environment. A polelike object detection algorithm was developed in the study. The algorithm’s accuracy was evaluated quantitatively using a manually collected reference (ie ground truth). In addition, the errors of the algorithm and the visibility of the objects in the MLS point clouds were assessed. This was one of the first studies of MLS point cloud processing that performed experimental tests and quantitative accuracy evaluations of a polelike object detection algorithm. The results of the study also implied slightly higher accuracies for the automated polelike object detection from MLS data than previous studies. In the Web of Science Core Collection, 142 publications have cited PI (22 September 2020).

**Publication II** reports a novel low-cost MLS system that can be installed on a mini-UAV or a car. My contribution in this publication was a case study in which the automated detection of polelike objects was investigated in a road environment using the MLS point clouds collected with the low-cost system. In the case study, the MLS system was installed on a car. Because the scanning geometry of the low-cost system differed from the one used in PI, a new algorithm was developed in PII that detected polelike objects from the low-cost MLS data. The algorithm’s accuracy was evaluated quantitatively in a small test area using a manually collected reference. The results suggested that it might also be possible to detect polelike objects from a point cloud collected using a low-cost system. In the Web of Science Core Collection, 190 publications have cited PII (22 September 2020).

**Publication III** reports a performance evaluation of the algorithm developed in PI in a larger test area.

**Publication IV** reports a study of general object recognition from MLS point clouds in a road environment. The objects to be recognised included the ground, building façades, trees, lampposts, traffic signs, cars, and pedestrians. The study’s main contribution was the comparison of different geometrical features that were used in a machine-learning-based classification of point cloud segments. To the best of the author’s knowledge, this was the first study in which advanced geometrical features, that is, local descriptor histograms (LDHs) and spin images, were used in the classification of MLS point clouds collected for surveying applications. The results suggested that the LDHs could increase the object classification accuracy compared to the state-of-the-art accuracy (an increase of 9.6 percentage points was observed with respect to a state-of-the-art
accuracy of 78.3%). The study also evaluated the accuracy of the segment classification and analysed the error sources of the whole object recognition processing chain. In the Web of Science Core Collection, 44 publications have cited PIV (22 September 2020).

**Publication V** reports a study of the automated detection of power lines and power line poles from MLS data. To the best of the author’s knowledge, the study was the first to investigate the feasibility of MLS in the mapping of power lines outside the road network. Algorithms were developed for the detection of power lines and wooden power line poles based on previous MLS power line studies. However, as the previous studies focused on urban and road environments, new features had to be developed for the algorithms to deal with the complications caused by the forest environment. The accuracies of the developed algorithms were evaluated quantitatively, using manually collected reference. In addition, the errors of the algorithms were analysed.

### 1.6 Structure of the thesis

After this introductory chapter, Chapter 2 provides the background to understand mobile laser scanning technology, and what was the state of the art in object detection and recognition from MLS point clouds before Publications I–V. Chapter 2 focuses on previous work relevant to the thesis, and therefore only reviews the literature closely related to the research questions of the thesis. Chapter 3 presents the general data analysis methods applied in the thesis, and explains the properties of the data sets used in Publications I–V. The chapter first briefly presents general object recognition, model selection and assessment, parameter tuning, and quantitative accuracy evaluation methods used in the thesis. The chapter then focuses on properties of the test sites, data collection equipment, and data preprocessing. Chapter 4 presents the main results of the thesis in relation to the research questions, that is, the developed algorithms and their testing. Chapter 5 discusses the results. It starts with the reliability and validity of the results, and then focuses on the theoretical implications of the thesis, in connection to the research question, by comparing the results with studies published both before and after Publications I–V. Lastly, the chapter discusses practical implications of the thesis and recommends topics for future study.
2. Literature Review

In this chapter, an overview of the mobile laser scanning technology is first presented. The most important studies related to the research questions of this thesis are then reviewed. The review in this chapter only includes articles that were published before Publications I–V. A comparison with studies reported after Publications I–V is presented in Chapter 5.

2.1 Mobile laser scanning

In a mobile laser scanning (MLS) system, a laser scanner is carried by a kinematic platform, such as a car or a backpack (Figs 2.1 and 2.2). The scanner collects three-dimensional (3D) geospatial data, and the data are typically in the form of 3D point clouds (Figs 2.3 and 2.4). The point cloud consists of point measurements of object surfaces (Fig. 2.5). The collection of 3D measurements is based on the lidar (light detection and ranging) principle, which means that a laser can be used to measure distances, that is, ranges. For example, a laser pulse is transmitted towards a target and is reflected from the target surface. The backscattered signal is observed using the receiver of the laser scanner, and the time taken to travel there and back is measured. Based on the travel time and speed of light, the distance from the target can be estimated. When the distance from the target and the direction of the laser ray are known, the 3D location of the target can be calculated with respect to the scanner origin. Scanning is typically performed by rotating the laser beam, using a rotating mirror, and the range is simultaneously measured, for example, a million times per second. As the platform is not static, its attitude needs to be determined to identify the laser beam’s direction. This is accomplished using an inertial measurement unit (IMU), or sometimes also simultaneous localisation and mapping (SLAM).

The above example of how the lidar principle is used in laser scanning describes the functioning of a pulse-based laser scanner, also known as a time-of-flight scanner. Another way to measure the distance or the range is to use a phase-based technique, where the object is illuminated with a continuous beam, and
Figure 2.1. FGI Roamer R3 mobile laser scanning system. Photograph by Antero Kukko.

Figure 2.2. FGI Akhka R2 backpack laser scanning system. Figure from [94]; photograph by Harri Kaartinen.
Figure 2.3. MLS point clouds of a power line corridor. Figure from V.
Figure 2.4. MLS point cloud of a road environment (from IV). © 2016 IEEE.

Figure 2.5. A tree in an MLS point cloud.
the distance measurement is based on amplitude modulation [69]. For example, the Faro Photon 120 laser scanner uses the phase-based principle, while the Riegl VQ-450 is a pulse-based scanner. Both are used in MLS systems.

Commonly, MLS systems use one or two scanners, in which the laser ray rotates in a vertical or tilted plane. The third dimension is given by the platform motion. Figures 2.6, 2.7, and 2.8 illustrate the FGI Roamer MLS system (Ch. 3) and its scanning geometry. Roamer was used in PI, PIII, and PIV. Roamer contains one scanner, and the scanning plane can be tilted in various angles. For example, in Figures 2.6 and 2.8, the direction of the scanning plane is 135 degrees backwards with respect to the driving direction and the normal orientation, which is vertical and perpendicular to the driving direction. The field of view in the scanning plane is 320 degrees (Fig. 2.7), and the gap points to the sky. Figure 2.8 illustrates how a vertical elongated object (pole) is scanned by Roamer. Several sweeps are retrieved from the pole that correspond to the consecutive revolutions of the scanner, also known as the profiles or scan lines. The scan line structure of the data can also be seen in the tree trunk in Figure 2.5.

The process of transforming the 3D point cloud into a global coordinate system is known as georeferencing. To georeference the data, the location and orientation of the scanner need to be known with respect to the coordinate system. Typically, this is achieved by using a global navigation satellite system (GNSS) (eg GPS) and an inertial measurement unit (IMU). A GNSS measures the loca-
Figure 2.7. FGI Roamer MLS system’s scanning geometry, top view (modified from I and from [68]).

Figure 2.8. An illustration of how the FGI Roamer MLS system scans a vertical pole, side view. (from I and modified from [68])
The point density of the laser scanning point cloud depends on the point measurement rate (PMR) of the scanner and driving speed, and it is also linearly dependent on the normal distance from the trajectory, that is, the route of the scanner. The PMR is defined here as the number of range measurements the scanner performs in a time unit. This is a valid measure for a phase-based scanner, which was the scanner type used in this thesis, because a phase-based scanner records only one range measurement, even if it detects several echoes from different surfaces. For time-of-flight scanners, a better measure is the pulse repetition rate (PRR), which equals the number of pulses sent by the scanner in a time unit. The number of measured points may be higher than the PRR, because the pulse-based system can record two or more returns for each sent pulse. Nowadays, more than one million points are typically measured per second by MLS systems, and state-of-the-art systems provide point clouds that contain more than 1,000 points per square metre at a 10 m distance from the scanner, with normal driving speeds in suburban areas.

In addition to point density, driving speed also affects the distribution of the point cloud. The faster the platform moves, the larger the distance between consecutive scan lines. The other factor that defines profile spacing is the frequency of the scanner’s mirror. In most of the datasets used in this thesis, the along-profile point density was much higher compared to the across-profile density, as can be seen from the gaps between the profiles in the tree trunk in Figure 2.5. However, as discussed in Chapter 5, mirror frequencies have grown considerably during the past decade, and the point density is therefore more uniform nowadays.

The accuracy of the 3D data depends strongly on the quality of the navigation satellite signals. In good satellite conditions, the accuracy is 2–3 cm with state-of-the-art systems [61, 45, 67]. However, for example, tall trees, high buildings, and tunnels cause difficulties that may reduce the accuracy even to a level of metres. In this case, one can use a more accurate IMU, SLAM (eg [72]), and reference targets to improve the georeferencing accuracy. However, even if the georeferencing accuracy is poor, the local accuracy of the point cloud, for example, in a 50 cm neighbourhood is always higher than 1 cm when a state-of-the-art system with a tactical-grade IMU is used [61].

2.2 Research question 1: How completely can polelike objects be detected from MLS point clouds in a road environment, and what is the quality of the results?

Before PI, the detection of polelike objects from MLS point clouds in a road environment had been studied in [20, 26, 92, 40, 48, 121, 96]. Manandhar and Shibasaki [92] utilised a vertical scanning pattern to detect vertical poles. Chen
et al. [26] studied the detection of traffic signs and signals. They segmented the point cloud and projected the segments onto a vertical plane. They then detected poles using principal component analysis. Brenner and Hofmann [20, 48] detected poles as cylindrical stacks, in which a kernel volume contained points and was surrounded by empty space. Munoz et al. [96] applied pointwise classification, and Markov random fields, to classify point clouds in several classes. However, the classification accuracy of linear structures was modest. Golovinskiy et al. [40] applied machine learning to classify point cloud segments in several categories, including various classes of polelike objects. During the writing of PI, I was unaware of the study by Golovinskiy et al. [40], and unfortunately therefore, their study was not cited in PI. Shi et al. [121] combined range data and images in a road sign detection method. Concerning other than laser-based mobile mapping systems, Doubek et al. [31] and Li et al. [79] used mobile mapping image data to detect vertical traffic infrastructure and lampposts, respectively.

Although most of the polelike objects are cylindrical in a road environment, this was not the case in the datasets used in Publications I–III. This was caused by the lower point density and inaccuracy of the 3D measurements. Therefore, the algorithms developed in this thesis were not based on the detection of cylindrical or conical shapes [93, 106, 117], or on detecting circular cross-sections [12, 15, 64]. In addition, not all vertical polelike objects have a circular cross-section, but the cross-section can also be rectangular, for example. Liang et al. [83] and Liang et al. [82] applied scan lines and surface normals, respectively, to find tree trunks from point clouds, but their methods were not applicable to our data due to differences in scanning geometry and point density, respectively.

The pole candidate extraction method in PI resembled the algorithm of Forsman [36], which detected overlapping circular point groups from horizontal scan lines to extract elongated objects. The difference of the algorithm in PI compared to Forsman [36] was that in PI no circularity assumptions were made. Bolles and Fischler [17] also fitted circles or ellipses to point segments, classified the segments, and clustered them to extract cylinders. In PI, a 3D cylinder mask was applied to separate poles from other candidates that were found in wall structures, for example. The idea of the cylinder mask resembled the kernel approach of Brenner and Hofmann [20, 48].

2.3 Research question 2: Is it possible to improve the accuracy of machine-learning-based object recognition from MLS point clouds in a road environment by using classification features that are based on the distribution of local descriptors, and what is the quality of the results?

In PIV, which was related to this research question, the aim was to first find and segment all objects in the point cloud and then classify them in different
categories. Therefore, I first briefly review studies in which several (i.e., more than two) object classes, other than the ground and buildings, were recognised from MLS point clouds in a road environment. As already mentioned in Chapter 1, I only concentrate on object-wise classification, and pointwise approaches are not included. The main objective related to this research question was the comparison of features to classify point cloud segments using machine learning. Thus, in the last part of this section, features used in the machine-learning-based classification of point cloud objects are reviewed.

Several approaches to the object recognition from point clouds had been studied prior to PIV. Awan et al. [13] applied graph matching, and Wang et al. [133] centre point voting, whereas several authors had applied machine learning [40, 119, 155] and semantic rules [101, 145, 147].

In PIV, machine learning was used to classify point cloud segments in several categories, such as cars, pedestrians, and lampposts. The inputs to the machine-learning algorithms are often termed features, and they are traditionally handcrafted by using prior information about the classification problem. More recently, deep learning [105, 152] and feature learning [30] methods have become more popular. These methods also learn the features from the data. However, in PIV, a more traditional support vector machine was applied with handcrafted classification features. I therefore review studies here published before PIV, in which the classification features were defined by expert knowledge and were not learned from the data. In addition, I limit the review to geometrical features, because these were of interest in PIV. General shape and distribution features had been used in most machine-learning-based point cloud object recognition studies. They describe the shape and distribution of a point cloud segment at a global level and contain, for example, the height and width of the object, as well as the number of points and mean height. In addition, more specific features had been developed prior to PIV. They contained features describing the distribution of height [103] and pointwise features (point feature histograms) [47, 24]. Other specific features developed prior to PIV were hierarchical descriptors [24], features describing contours and curvature [18], spin images [40, 129, 24], Fourier histograms [24], and LLmaps [155].

In PIV, local descriptor histograms (referred to as point feature histograms in [47]) and spin images were applied for MLS point cloud data for surveying applications for the first time. Previously, they had been tested in studies related to robotics, general point cloud processing, and autonomous driving [40, 47, 24]. See more details in PIV, Section I.
2.4 Research question 3: How completely can power lines be detected from MLS point clouds outside the road network, and what is the quality of the results?

Before PV, automated MLS-based power line mapping had been studied in [27, 42, 63, 141, 139]. The paper by Xu and Wang [139] was not included in PV because of the short time span between the publications of [139] and PV. In all the aforementioned studies, the test areas were situated in urban or road environments. Therefore, to the best of my knowledge, PV was the first study that investigated the feasibility of MLS for the automated detection of power lines outside the road network.

Like methods in [27, 42, 63, 141], the power line detection algorithm developed in PV first extracted candidate points that would belong to a power line with a high probability, and this phase was followed by the detection of the power line. The candidate extraction was performed in PV, using the same principles as in [63]. Horizontal lines were then sought, using a voting method as in [27, 42, 141]. Finally, power lines were detected from the lines, using a method that extracted connected components from a point set and removed false detections by not accepting large jumps in the vertical direction. The false detection removal was a development compared to previous MLS power line studies. The extension enabled the removal of commission errors typically found in the forest. Xu and Wang [139] first divided the point cloud into components that contained points of only one object, using a robust maximum a posteriori estimator, and then detected power lines from the components.
3. Methods and Materials

In this chapter, the methods used in this thesis found in the literature are listed first. The methods are related to object recognition from point clouds, model selection and assessment, parameter tuning, and accuracy evaluation. The properties of the test sites and equipment that were used to collect data are then described. At the end of the chapter, a short description of data preprocessing is included. The new methods developed in this thesis are presented in Chapter 4.

3.1 Methods for object recognition from point clouds, model selection and assessment, and parameter tuning

The methods applied in this thesis related to object recognition from point clouds are listed in Table 3.1. In addition to references to the literature, the table lists original publications included in this thesis, where corresponding methods have been applied.

The model selection and assessment and parameter tuning methods applied in this thesis are listed in Table 3.2. In addition to references to the literature, the table lists the original publications included in this thesis, where corresponding methods have been applied.

3.2 Methods for accuracy evaluation

In the following, reference targets detected by an algorithm are referred to as ‘true positives’, and targets missed by an algorithm as ‘omission errors’ or ‘false negatives’. Objects falsely detected by an algorithm – that is, the algorithm has detected an object when no object exists – are referred to as ‘commission errors’ or ‘false positives’. Let \( n_{\text{ref}} \) denote the number of all reference targets, \( n_{\text{TP}} \) the detected reference objects by an algorithm, and \( n_{\text{FP}} \) the commission errors. The recall of the detection [100], also known as the completeness, is defined as follows:
Table 3.1. Methods related to the object recognition from point clouds applied in this thesis. CC stands for connected-component, PCA for principal component analysis, SVM for support vector machine, LDH for local descriptor histogram, and RANSAC for random sample consensus.

<table>
<thead>
<tr>
<th>Task</th>
<th>Methods</th>
<th>Publications and references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Segmentation</td>
<td>CC labelling</td>
<td>IV, V, [40, 115]</td>
</tr>
<tr>
<td></td>
<td>Surface growing</td>
<td>IV, [131]</td>
</tr>
<tr>
<td></td>
<td>Scan line segmentation</td>
<td>I, [122, 56, 55, 49]</td>
</tr>
<tr>
<td>Shape description</td>
<td>PCA</td>
<td>IV, [52, 16]</td>
</tr>
<tr>
<td></td>
<td>Local descriptors</td>
<td>IV, [47, 73]</td>
</tr>
<tr>
<td>Classification</td>
<td>SVM</td>
<td>IV, [16]</td>
</tr>
<tr>
<td></td>
<td>LDH</td>
<td>IV, [47]</td>
</tr>
<tr>
<td></td>
<td>Spin image</td>
<td>IV, [58, 40]</td>
</tr>
<tr>
<td>Shape retrieval</td>
<td>RANSAC</td>
<td>V, [35, 17, 22, 117]</td>
</tr>
<tr>
<td></td>
<td>Hough transform</td>
<td>II, [32, 50]</td>
</tr>
</tbody>
</table>

Table 3.2. Model selection and assessment and parameter tuning methods applied in this thesis.

<table>
<thead>
<tr>
<th>Method</th>
<th>Publications and references</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grid search</td>
<td>V, IV, [107, 51]</td>
<td>Hyperparameter tuning</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Parameter tuning</td>
</tr>
<tr>
<td>Backward elimination</td>
<td>IV, [44]</td>
<td>Variable selection</td>
</tr>
<tr>
<td>Nested cross-validations</td>
<td>IV, [66]</td>
<td>Model selection</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Model assessment</td>
</tr>
<tr>
<td>Monte Carlo sampling</td>
<td>IV, V, [16]</td>
<td>Model selection</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Model assessment</td>
</tr>
<tr>
<td>Probability theory</td>
<td>V, [16]</td>
<td>Parameter tuning</td>
</tr>
<tr>
<td>Wilk–Shapiro test for normality</td>
<td>IV, V, [112, 111]</td>
<td>Repeatability and reliability</td>
</tr>
</tbody>
</table>
Recall measures the extent to which the reference targets are detected by an algorithm. The precision of the detection [100], also called the correctness, measures the extent to which the targets detected by an algorithm are correct, that is, belong to the reference. The mathematical definition is

\[
\text{Recall} = \frac{n_{TP}}{n_{ref}}.
\]

\[
\text{Precision} = \frac{n_{TP}}{n_{TP} + n_{FP}}.
\]

In the point cloud segment classification, the classifier classifies the segments in two or several classes. The classification accuracy used in PIV measures the extent to which the segments are classified correctly. This is defined as the ratio of correctly classified segments to all segments. The confusion matrix [100] (sometimes referred to as the contingency table) describes how the classes are mixed in the prediction.

### 3.3 Test sites and data collection equipment

This section lists the properties of the test sites and equipment that were used to collect the data used in this dissertation.

The algorithms developed in the thesis were tested at five test sites (A–E). Table 3.3 lists the main properties of the test sites, in which publication they were used, and indices of figures in the original publications. All suburban test sites were in Espoo, Finland. At all suburban test sites, the platform of the MLS system was a car, and it moved along streets in flat areas (i.e., no hills). In this thesis, only data collected in one driving direction was used at the suburban test sites. The suburban test sites contained traffic signs, lampposts, trees and other vegetation, cars, pedestrians, and buildings close to the street where the MLS system was moving. Test site C corresponds to test area B in PIII. Two of the suburban test sites, that is, C and D, contained crossroads; the other two suburban sites were straight stretches of road. The only rural test site (E) was in Loviisa, Finland. The test site was a power line corridor, outside the road environment in a rural area that contained both forest and farmland. A 20 kV power line that contained wooden poles was located in the power line corridor. The scanner and navigation system were installed either on an ATV or in a personal backpack. The widths of all test sites in the direction perpendicular to the movement of the platforms were significantly lower than the maximum measurement distances of the laser scanners.

Table 3.4 lists the properties of the four MLS systems that were used to collect data at the test sites, namely, FGI Roamer (Road environment mapper) [70, 69], FGI Sensei (II), FGI Roamer R2 [62], and FGI Akhka R2 [86]. All four systems were developed at the Finnish geospatial research institute (FGI). The Sensei system was low-cost. The Akhka R2 was a backpack MLS system, whereas
Roamer and Roamer R2 used a motorised platform, such as a car or an ATV. The Akhka R2 and Roamer R2 systems used the same scanner and navigation system. The Sensei system used a car and a UAV as platforms (II), and in this thesis, only a car was used.

In all systems, one laser scanner and a navigation system were mounted to a rigid platform, which could be installed, for example, on a car, boat, ATV, or personal backpack. All navigation systems used in this thesis integrated a GNSS and IMU. In the Roamer, Roamer R2, and Akhka R2 systems, a tactical-grade IMU was used. In each system, 2D profiles were scanned, while the movement of the platform provided the third dimension. All systems except for the Sensei system scanned in one plane, which was perpendicular to the direction of the movement but could be tilted backwards at various angles. The field of view of these systems was 305°–320°, and the ‘blind zone’ could point either up or down, depending on the needs of the application. The Sensei system collected four layers simultaneously, effectively collecting four vertical profiles during one sweep. Sensei scanned one side of the road. The laser scanners and navigation systems of the MLS systems are listed in Table 3.5. The Sensei system was the only one using a pulse-based laser scanner (Ch. 2), while the laser scanners of all other systems were phase-based.

The elevation and planimetric accuracy of the point clouds of the Roamer system were approximately 2 cm in good GPS conditions [61]. The accuracy of the Roamer system was comparable to that of the most prominent commercial systems at the time of data collection [61]. The 3D accuracy of the Akhka R2 point clouds was better than 4 cm when using reference targets [67]. It was also found (V) that the drifting of the positioning in the Akhka R2 and Roamer R2 systems was less than 10 cm at a 50 m distance along the trajectory in the forest and in good GNSS conditions. Even if the connection to the navigation satellites was poor, the local relative error between neighbouring points was lower than 1 cm in the Roamer, Roamer R2, and Akhka R2 systems. The point clouds of the low-cost Sensei system naturally had a lower accuracy. The planimetric and vertical errors of single points in the Sensei point clouds were approximately 20 cm and 10 cm, respectively (II). In all systems, the quality of the GNSS signal was the most important factor affecting the accuracy of the positioning. Even when using the current state-of-the-art systems, the positioning solution may drift even several metres in the event of a GNSS outage. The IMU can compensate for the lack of satellite signals only in short time intervals due to error cumulation. Roamer, Roamer R2, and Akhka R2 contained a small-footprint laser scanner. The footprint of the Faro Focus3D used in the Roamer R2 and Akhka R2 was 0.73 cm at a 25 m distance from the scanner. The footprint of the Ibeo Lux scanner of the Sensei system was approximately 3.5 cm in the horizontal direction and 35 cm in the vertical direction when the distance from the scanner was 25 m.
Table 3.3. Properties of the test sites. The publication column also contains the indices of the figures in the original publications, where either the point cloud or test area is shown.

<table>
<thead>
<tr>
<th>Test site (Fig.)</th>
<th>Publication</th>
<th>Location</th>
<th>Length (m)</th>
<th>Width (m)</th>
<th>Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>A I (2)</td>
<td>Espoonlahti</td>
<td>450</td>
<td>60</td>
<td>Suburban</td>
<td></td>
</tr>
<tr>
<td>B II (5,6,8)</td>
<td>Espoonlahti</td>
<td>70</td>
<td>20 (d)</td>
<td>Suburban</td>
<td></td>
</tr>
<tr>
<td>C III (2,5)</td>
<td>Espoonlahti</td>
<td>800</td>
<td>60</td>
<td>Suburban</td>
<td></td>
</tr>
<tr>
<td>D IV (2,6)</td>
<td>Espoonlahti</td>
<td>900</td>
<td>40</td>
<td>Suburban</td>
<td></td>
</tr>
<tr>
<td>E V (1–3)</td>
<td>Loviisa</td>
<td>1,750</td>
<td>40</td>
<td>Rural</td>
<td></td>
</tr>
</tbody>
</table>

(a) Inside brackets, the indices of the figures in the original publications
(b) The approx. length along the trajectory
(c) The maximum distance from the trajectory equalled width/2
(d) Only one side of the road was scanned and, the maximum distance from the trajectory was 20 m.

Table 3.4. The MLS systems used in this thesis and their main characteristics.

<table>
<thead>
<tr>
<th>Test site</th>
<th>MLS system</th>
<th>Platform</th>
<th>PMR (kHz)</th>
<th>Mirror (Hz)</th>
<th>Profile spacing (cm)</th>
<th>Scanning plane slope (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A Roamer</td>
<td>Car</td>
<td>120</td>
<td>15</td>
<td>37</td>
<td>45</td>
<td></td>
</tr>
<tr>
<td>B Sensei</td>
<td>Car</td>
<td>38 (1)</td>
<td>NA</td>
<td>8 (2)</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>C Roamer</td>
<td>Car</td>
<td>120</td>
<td>30</td>
<td>28</td>
<td>45</td>
<td></td>
</tr>
<tr>
<td>D Roamer</td>
<td>Car</td>
<td>120</td>
<td>48</td>
<td>17</td>
<td>45</td>
<td></td>
</tr>
<tr>
<td>E Roamer R2</td>
<td>ATV</td>
<td>488</td>
<td>95</td>
<td>1.7–6.8</td>
<td>80–85</td>
<td></td>
</tr>
<tr>
<td>E Akhka R2</td>
<td>Backpack</td>
<td>488</td>
<td>95</td>
<td>1.2</td>
<td>75–85</td>
<td></td>
</tr>
</tbody>
</table>

(1) Assuming one return per pulse per layer
(2) Spacing between consecutive layers (II) at an approx. 5 m distance from the scanner
<table>
<thead>
<tr>
<th>MLS system</th>
<th>Reference, Fig.</th>
<th>Scanner</th>
<th>Navigation system</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roamer</td>
<td>I, 1</td>
<td>Faro LS 880HE80</td>
<td>NovAtel DL-4plus GPS Honeywell HG1700AG58 IMU</td>
</tr>
<tr>
<td></td>
<td>IV, 6</td>
<td>Faro Photon 80</td>
<td>NovAtel DL-4plus GPS Honeywell HG1700AG58 IMU</td>
</tr>
<tr>
<td>Sensei</td>
<td>II, 3</td>
<td>Ibeo Lux</td>
<td>NovAtel SPAN-CPT</td>
</tr>
<tr>
<td>Roamer R2</td>
<td>[62], 1</td>
<td>Faro Focus$^{3D}$ 120S</td>
<td>NovAtel SPAN Flexpak6+UIMU-LCI</td>
</tr>
<tr>
<td>Akhka R2</td>
<td>[86], 1, 3</td>
<td>Faro Focus$^{3D}$ 120S</td>
<td>NovAtel SPAN Flexpak6+UIMU-LCI</td>
</tr>
</tbody>
</table>

(1) Reference and index of the figure in the reference that contains a photograph of the MLS system.
3.4 Georeferencing and preprocessing of the MLS data

This section briefly explains how the data were georeferenced and preprocessed. Except for PI, all the collected MLS data were georeferenced into the ETRS-TM35FIN map coordinate system, and ellipsoidal heights were used for point elevations. Direct georeferencing (eg [69]) was applied in all publications included in this thesis – that is, no ground reference points were needed and the position and orientation of the platform were determined using a GNSS and IMU. In PI, the point cloud was first georeferenced in the global WGS 84 coordinate system. Because the terrain was flat, the point cloud was then rotated, such that the horizontal plane corresponded to the $xy$-plane, and the positive $z$-axis pointed to the sky (I, Sec. 2.2). The rotations were performed using the principal component analysis. As a result of this transformation (and terrain flatness), vertical structures were parallel to the $z$-axis.

At test sites C, D, and E, stray points that appeared falsely in the air were filtered before object extraction.

Because of the moving restrictions in the forest (eg large rocks, rugged terrain), the platform speed was occasionally slow in the power line study reported in PV. This resulted in an inhomogeneous point density in the point cloud data, which complicated the automated point cloud interpretation. Data quality was improved by removing points that were collected when the platform speed was less than 2.5 cm/s.
4. Results

In this chapter, the results of this thesis are presented. The results are divided into sections, according to research questions.

4.1 Research question 1: How completely can polelike objects be detected from MLS point clouds in a road environment, and what is the quality of the results?

This section describes the developed algorithms for the detection of vertical polelike objects from MLS point clouds in a road environment. In addition, the testing of the algorithms and analyses of the results are presented. The visibility of poles in the MLS data is also analysed.

Two algorithms were developed in this thesis that detected the vertical polelike objects from mobile laser scanning point clouds in a road environment. The first algorithm (hereafter, Algorithm 1) was reported and tested in PI and further tested in a larger test area in PIII. The data that were used in the development and testing were collected using the FGI Roamer, which could be considered a state-of-the-art MLS system at the time of data collection (Ch. 3).

By performing field measurements, it was also possible to investigate how completely the state-of-the-art MLS technology recorded the polelike objects in a road environment.

The second algorithm (hereafter, Algorithm 2) was reported in PII. It was developed to be used with data collected using the low-cost Sensei MLS system.

4.1.1 Algorithm for the polelike object detection

Algorithm 1 was based on first finding candidate point clusters for vertical polelike objects and then classifying the objects based on several rules and thresholds. In the candidate detection phase, short sweeps of narrow poles were first sought in individual scan lines. The sweeps were then clustered across scan lines by searching for overlapping sweeps in neighbouring scan lines and the horizontal plane. The objects were sometimes split into two or more
clusters, and the clusters were thus merged by using the shape of a vertical pole as a criterion. The clusters acted as pole candidates classified as vertical polelike objects and other objects based on the following characteristics: length; number of sweeps; shape; orientation; and point density in the neighbourhood. Publication I, Section 3 contains a more detailed description of Algorithm 1.

4.1.2 Testing of the polelike object detection algorithm

Algorithm 1 was tested at test sites A and C (Ch. 3), which were in a suburban area. Test site C was referred to as ‘test area B’ in PIII.

At both test sites, the reference against which the performance of the algorithm was evaluated contained all polelike objects found in the field visible in the point cloud. However, the length of the pole needed to be more than 1 m, and the horizontal distance of the object from the trajectory had to be less than 30 m. A training dataset and an independent test dataset were used at test site C to avoid the parameters being tuned with the same data as the method performance was evaluated. The training set comprised 99 targets, and its purpose was to tune the parameters of Algorithm 1. The separate test set was used to evaluate the accuracy of the algorithm. At test site A, the method was validated to identify possible overfitting effects (I, Sec. 4.3). The number of polelike objects in the reference of test site A and the reference of the independent test set of test site C was 148 and 330, respectively.

The results of the testing of Algorithm 1 can be found in PI, Section 4 and PIII, Section 3. In PI and PIII, the terms ‘detection rate’ and ‘correct detections (%)’ were sometimes used to denote recall and precision, respectively. The tests at site A were those performed in PI, and the results were also summarised in PIII. The main results of the accuracy evaluation can be found in PI, Table 3, 4, and 5, and in PIII, Table 1. The completeness of the detection was 77.7% at test site A, and 69.7% at test site C. The precisions were 81.0% and 86.5% at test sites A and C, respectively.

In approximately half the omission errors at test sites A and C, points existed around and close to the pole or tree trunk due to vegetation and branches. The neighbouring points prevented the detection of the object, because the point density was too high in close proximity to the pole. Single sweeps on the scan lines having too few points also caused the missing of several objects. In addition, some cars were parked on the side of the road, shadowing the lower part of a pole or trunk, making it difficult to detect the target.

Building structures and some hoardings (advertising boards) that resembled the shape of a pole in the point cloud (eg I, Fig. 9) caused most of the false detections.
4.1.3 The ability of the MLS technology to map polelike objects in a road environment

The accuracies listed in Section 4.1.2 were gained using a reference which contained only objects that were visible in the point cloud data. They therefore measure the performance of the algorithm, but do not consider how completely MLS technology records objects found in the field. Before the creation of the reference, all polelike objects were mapped in the field by human operators. At test site C, the mapping was performed from dense TLS point clouds that covered the test area thoroughly. It could therefore be considered accurate as a field reference. The existence of each object in the MLS point cloud was then manually checked by a human operator. Approximately 86% and 74% of the targets found in the field were also identified in the point cloud data at test sites A and C, respectively. This imposes an upper limit for the completeness that the MLS technology can achieve in automated object detection. When all polelike objects found in the field (ie the field reference) are considered, the recalls of the automated detections were 67.1% and 51.8% at sites A and C, respectively. The scanner was unable to record all objects because of occlusion, and because the point density decreases linearly with respect to the distance from the trajectory.

4.1.4 Detection of polelike objects from point clouds collected using a low-cost MLS system

Algorithm 2 was developed using MLS data that were collected using the low-cost FGI Sensei system (Ch. 3). Algorithm 1 was used as a starting point when developing Algorithm 2, but modifications were needed, because the scanning geometry of Sensei differed from that of the Roamer system.

Sensei scans one side of the road, and the scanning plane is vertical. Vertical poles therefore consist of vertical profiles in the point cloud. First, each scan line was divided into line sections using the Hough transform [32, 50] and connected-component labelling [40, 115]. Second, pole candidates were extracted by grouping vertical line sections based on horizontal pairwise distances. Third, vertical polelike objects were classified based on three rules: 1) the candidate must be vertical; 2) the candidate must have an elongated shape; 3) the height of the candidate must be at least 1 m.

Algorithm 2 was tested at test site B (Ch. 3). The reference contained 21 poles and tree trunks that were found from the point cloud of the test area in a manual check. Of the 21 reference objects, Algorithm 2 detected 19. Three false positives were also found, resulting in 90% completeness and 86% correctness. Neither of the two missed objects had a polelike shape in the point cloud, based on the shape descriptors of the algorithm.
4.2 Research question 2: Is it possible to improve the accuracy of machine-learning-based object recognition from MLS point clouds in a road environment by using classification features that are based on the distribution of local descriptors, and what is the quality of the results?

An automated object recognition workflow was developed in PIV that was based on basic principles published previously, for example, in [101, 40]. The workflow was used first, to compare classification features, second, to analyse segment classification errors, and third, to evaluate the accuracy of the whole object recognition workflow. The workflow was tested at test site D (Ch. 3).

4.2.1 Object recognition workflow

First, the ground and buildings were retrieved and removed in the workflow of PIV. The remaining points contained objects of interest, such as traffic signs, cars, lampposts, and pedestrians. The ground and buildings were extracted using the surface growing approach to find smooth (ground) and planar (buildings) surface patches. Rasterisation into a binary image and minimum bounding rectangles were also applied in the building extraction. Second, connected-component labelling was applied to the remaining point cloud, and classification features were extracted from each identified component, that is, point cloud segment. Third, a rough classification was applied where, for example, objects that were too large or too small were removed (eg stray points in the air). Fourth, the support vector machine (SVM) classifier was used to classify the segments using the features extracted in the second step as an input. Fifth, the centre of mass was calculated for each classified segment to estimate its location. As a result, a set of classified objects with a location estimate was retrieved.

4.2.2 Comparison of features and error analysis

A total of 350 point cloud segments was retained after the rough classification at test site D. They were classified manually in seven categories: trees; lampposts; traffic poles (including traffic lights, traffic signs, and signposts); cars; pedestrians (and cyclists); hoardings; and others (undefined objects). From each segment, three types of classification feature were extracted: general shape and point distribution features; local descriptor histograms (LDHs); and spin images. The general shape and point distribution features represented the current state-of-the-art. The feature types were compared in the classification of the point cloud segments. Local descriptor histograms combined with general shape and point distribution features were chosen as the best classification model (IV, Tab. II, Sec. IV-A). The classification accuracy of this model was 87.9%. The local descriptor histograms improved the state-of-the-art accuracy (only general features) by 9.6 percentage points.

‘Undefined objects’ was the most problematic object class (IV, Tab. III). It
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caused most of the classification errors. Especially trees, traffic poles, and pedestrians were classified as undefined, and vice versa.

The largest error source in the whole object recognition workflow was the segmentation method, that is, connected-component labelling (IV, Tab. IV). Due to undersegmentation, many objects were missed. In addition, the ground extraction algorithm failed to find the ground level in some locations, which caused omission errors.

4.3 Research question 3: How completely can power lines be detected from MLS point clouds outside the road network, and what is the quality of the results?

An algorithm was developed and tested in PV that detected power lines from MLS point clouds (hereafter, Algorithm 3). The performance of the algorithm was evaluated in a rural area, outside the road network, both in a forest and an open field, namely, farmland. The automated detection of wooden power line poles was also studied in the same environment using algorithms found in the literature. Two kinematic platforms were used to carry the laser scanner, namely, a personal backpack (personal laser scanning or PLS [53]) and an all-terrain vehicle (ATV). The comparison was performed between the two platforms and between the two land cover types, that is, forest and farmland.

4.3.1 Algorithm for power line detection

The goal in PV and hence that of Algorithm 3 was to find the horizontal (two-dimensional, 2D) locations of the power lines (conductors). This was achieved by first finding power line candidate points, and second, by finding power lines from the candidates. The power lines were extracted from the candidates using RANSAC, which was followed by a connected-component search. To account for the issues in the forest (V, Sec. 3.2), the connected power line search (CPLS) method was developed that labelled connected power line segments from the lines found using RANSAC. Publication V, Section 4 contains a more detailed description of Algorithm 3.

4.3.2 Testing of the power line detection algorithm

Algorithm 3 was tested at test site E (Ch. 3). The trajectory of the ATV was situated in the open field for the most part, whereas the PLS was used mostly in the forest. The reason for these choices was that the ATV is faster in the open field, but may be slower or unable to move at all in the forest.

Points further than 20 m from the trajectory were removed. This hastened the data processing and reduced the number of commission errors, which were found especially in the forest surrounding the power line. The parameters of the
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algorithms were tuned using a training area, while their accuracy was evaluated using a separate test area (V, Fig. 1). Of the whole test area, approximately 770 m were scanned using the ATV, and 1,065 m using the backpack. Inside the test area, two sub-areas were selected, that is, a forest sub-area and an open field sub-area. The forest sub-area was scanned using both platforms, the open field area using only the ATV. The performance of the power line mapping between the two land cover types (forest and open field) and between the two platforms was compared using the sub-areas.

The accuracy evaluation was performed pointwise and by sampling points along the reference and detected power lines. The reference was collected manually from the point clouds. For each conductor in each span, a 2D line segment was identified. The horizontal locations of the poles were also collected. If the distance between the detected power line and the reference was shorter than 10 cm, the detection was considered successful. For the poles, the corresponding distance was 0.5 m.

The accuracies of the power line mapping are presented in PV, Table 1. In the power line mapping, the precision and recall were 93.6% and 93.3%, respectively, in the whole test set. In practice, no difference could be seen in the accuracies of the two platforms. Power line mapping in the open field was more successful than in the forest. In the forest, the accuracies were lower because of the weaker GNSS signal and the more heterogeneous point density. The terrain was often rugged and contained large rocks. The speed of the MLS platform (backpack or ATV) therefore varied greatly, which caused variation in the point density.

The error analysis of the power line mapping is presented in PV, Section 5.4. The positioning errors of the MLS system caused most of the omission and commission errors (approx. 60%–70%) in the power line mapping. Heterogeneous point density, false power line candidate points, and pole locations also caused a considerable number of commission errors. The low number of power line points, point cloud edges, stray points in the air, and branches around the conductors were the other main reasons for missing the reference conductors.

Of the 46 reference power line poles manually found in the test area, 79% were detected by the algorithm (V, Tab. 2). The corresponding precision was 96%. The number of omission errors was therefore significantly higher than that of commission errors. Again, the lack of a high-quality GNSS signal caused problems, and the accuracies were 5–7 percentage points higher in the ATV test set than in the PLS test set, which was mostly in the forest.
5. Discussion

In this chapter, the reliability of the results is first discussed, followed by an analysis of the theoretical and practical implications of this thesis. At the end of the chapter, recommendations for future research are given.

5.1 Reliability and validity of the results

All except one of the test sites were situated in the Espoonlahti district of Espoo, Finland. Three of the Espoonlahti sites were on the same street and partly overlapped. There might therefore be a criticism that the variability at test sites was not particularly high. However, test sites C and D proved quite challenging considering the detection of trees (see IV and discussion below) and the amount of vegetation that caused undersegmentation errors, for example.

The number of polelike objects in the references of PI and PIII that were used to evaluate the accuracy of the methods was 148 and 330, respectively. This is comparable with several other MLS pole detection studies [21, 101, 145, 81, 110, 34]. However, some studies have contained test sets of more than a thousand objects [147, 125, 152]. Test site B, for pole and tree trunk detection from the low-cost MLS data in PII, was quite small. The number of corresponding reference targets was therefore also low, and the reliability of the pole detection results in PII may be questioned – especially because the same data were used to tune the parameters of the algorithm and evaluate its performance. However, the results are at least promising, considering the application of a low-cost system to pole detection.

In PIV, 350 segments were used to test the classification features, and the objects were divided into seven categories. Although the counts in the different classes varied greatly, five out of seven categories contained more than 30 examples. This is comparable with two other studies that applied local descriptor histograms (LDHs) in 3D point cloud classification [24, 47]. Chen et al. [24] had 631 examples in 15 categories after they had combined classes that had only a few examples. Himmelsbach et al. [47] had 284 segments, which is lower than in PIV, but they had significantly more samples per class, because they
performed a binary classification.

In the power line detection in PV, the combined length of the test sets along the power line was more than 1,490 m when the backpack’s area was excluded in which it overlapped the ATV data. This is longer than or comparable with the test sets in previous MLS power line studies [141, 42, 27, 139] that evaluated the accuracy of their method quantitatively.

In this thesis, the focus was on optimising the quality of the outputs of the algorithms (eg classification accuracy), and the computational efficiency, referring to the CPU (central processing unit) time, was less important. This is a typical approach in remote sensing, where computations are usually performed after the data collection, and it is enough that the data can be processed in a reasonable time. For example, Lindenbergh et al. [88] suggest that it is enough that the time needed to process the data does not exceed the duration of the data collection. This thesis follows a similar approach, and computational efficiency was part of method development, to keep the computation times acceptable. This can also be seen in several sections of Publications I–V, in which computational efficiency was mentioned or analysed. However, not all of the Publications I–V reported computation times of the algorithms, because the codes were not optimised, nor was parallel computing applied, and algorithms were implemented using Matlab software. Parallel computing may have considerably hastened the processing in many cases. Matlab, on the other hand, is efficient in developing algorithms, but may sometimes be computationally inefficient compared to C or C++, for example.

The generality of the point cloud processing algorithms depends partly on the number of different data sources they need. For example, Algorithms 1 and 2 in PI and PII, respectively, utilised the row–column information of the laser scanner, that is, how the point cloud was divided into scan lines, and how the points were ordered along the scan lines. However, in general, the scan line (ie profile) information is not always available, which limits the use of Algorithms 1 and 2. Extra data sources were used in this thesis to improve the performance of the algorithms, and, for example, the use of the scan line information improved the computational efficiency of Algorithms 1 and 2. Therefore, in general, balancing is needed between the generality and the performance when developing algorithms.

In this thesis, Algorithms 1 and 2 were the least general, because they required the profile information. The methods developed in PIV and PV work with unstructured point clouds, but they use the intensity of the returning pulses to filter stray points in the preprocessing phase. Scan line segmentation is quite efficient at removing isolated points, and stray point filtering was therefore unnecessary in Algorithms 1 and 2. The pole detection algorithms assumed a certain scanning geometry – tilted scan lines in Algorithm 1, vertical scan lines in Algorithm 2. A fusion of the algorithms might be completely independent of the scanning geometry.

Another issue is the combination of point clouds collected in the same area
in a corridor but at different time instances – for example, in opposite driving
directions. As discussed in [101, 95], inaccuracies in the georeferencing and point
cloud registration mean that in some cases, it may be beneficial to detect the
objects from point clouds collected in one driving direction and do the merging
at object or feature levels – as in the multi–single-scan method of Liang and
Hyyppä [84]. The algorithms may thus utilise the high sub-centimetre-level
local accuracy of the point clouds.

The trajectory information, that is, the route of the scanner, was used to limit
the test areas in this thesis. The trajectory could also be used, with the time
stamps of the points, to divide the data into profiles. The scan line information
would then no longer be needed. The trajectory and the time stamps are more
often available than the profile information, and their use in retrieving the scan
lines would improve the generality of the pole detection algorithms in PI and
PII. The time stamps would also be beneficial in dividing the MLS data into
blocks, such that the block sizes and overlapping between neighbouring blocks
could easily be defined by the user.

If the same data are used to tune the parameters of the algorithms and test
their performance, the evaluation results may be biased and give over-optimistic
estimates of the accuracy of the methods, for example. In PI, a validation was
performed to ensure that no severe overfitting of the parameters to the data had
happened. In PII, the test data were of modest size, and the same data were used
both for parameter tuning and accuracy evaluation. In PIII and PV, separate test
and training areas were applied. In PIV, nested tenfold cross-validations with
stratification were performed, as suggested by Krstajic et al. [66] and Kohavi
[65], to retrieve unbiased results. This ensured that the model assessment was
performed with different data than had been used in the training of the model
or model selection. Nested cross-validations were performed instead of separate
training, validation, and test datasets, because the amount of data would not
have been large enough to be split into three separate sets.

The results of this thesis could also be criticised in the sense that the same
datasets were used to develop and test the algorithms. The choices made in
method development may therefore have been adapted to the datasets, and
the results may be over-optimistic to some extent. For example, when I chose
between the radial basis function kernel and the linear kernel in the SVM-based
classification in PIV, I used all 350 point cloud segments. In PV, the power line
detection algorithm was also developed using the whole dataset, after which the
training set was separated from the data for parameter tuning.

In PIV, the evaluations depended on how the cross-validation folds were ran-
domly selected. In PV, the RANSAC algorithm contained random sampling.
To eradicate sensitivity to single random samples, Monte Carlo sampling was
utilised in PIV and PV. In PIV, the evaluation based on nested cross-validations
was repeated 67 times, each with a different random cross-validation fold divi-
sion. In PV, the power line detection was repeated ten times using the training
set, and 100 times using the test set. After repeating the cross-validations and
power line detections, the samples were tested for normality, and the distributions were summarised by their means and standard deviations (IV, Sections II-J and IV-A; V, Sections 5.1 and 5.3).

The machine-learning-based methods could be criticised, because new manually collected training data are typically needed with new datasets. However, as discussed in PIV, the non-learning methods also often need parameter tuning when applied to new datasets, which requires manual work and expertise on the algorithms. Moreover, training data collection is quite straightforward in the point cloud segment classification. If an easy-to-use tool that also uses images were implemented, the training data collection could be a relatively quick process that required no knowledge of the algorithms.

The results’ sensitivity concerning the values of the parameters of the algorithms was analysed to some extent, but not extensively. In PI and PIII, the parameters were tuned using two different datasets, and it was found that the selected parameter values were very similar in both datasets. Only one scan line segmentation parameter was changed, probably due to a difference in the mirror frequency between datasets. This provides some clue of the robustness of the method, considering the parameter sensitivity. In PIV, the effect of the voxel size on the segmentation result was analysed. However, both the pole detection algorithm (I) and the object recognition workflow (IV) contained around ten parameters or thresholds. In PV, Section 5.2, a more thorough parameter sensitivity analysis was performed. However, no control parameters [74] were defined in the algorithms, which would be helpful when applying the methods to new datasets. More discussion of the use of control parameters can be found in Section 5.4.

5.2 Theoretical implications

This section compares the results of this thesis with those of other studies: the contribution of the thesis compared with previous studies, and how the thesis contributes to later studies. In addition, this section discusses how others have dealt with the challenges of the automated processing of MLS point clouds faced in this thesis.

The test sites of different studies typically have different characteristics. Some sites may be more complex due to a large amount of vegetation and objects attached to each other, for example. The equipment used to collect the point clouds also differ. The quality of the point clouds (eg the density and the 3D accuracy) therefore varies across the studies. Moreover, the studies’ research questions are not always identical. For example, different object categories may be used in object recognition, or the 2D instead of 3D locations of objects are detected. The test areas and references may also be defined differently (eg the maximum distance from the trajectory; selecting only tall poles). A comparison across the studies is therefore complicated.
In general, the testing of the algorithms developed in this thesis revealed some challenges in the automated processing of MLS point clouds. These results can be utilised in future to indicate directions for new studies to improve the accuracy of point cloud processing algorithms. The rest of this section is divided in accordance with the research questions.

5.2.1 Research question 1: How completely can polelike objects be detected from MLS point clouds in a road environment, and what is the quality of the results?

Publication I was one of the first MLS studies that, with Golovinskiy et al. [40] and Hofmann and Brenner [48], quantitatively evaluated the accuracy of the automated polelike object detection in a road environment. In Golovinskiy et al. [40], the completeness of the detection varied between 40% and 91%, and the correctness between 45% and 79%, across the five polelike object categories (short posts, lampposts, light standards, traffic lights, and tall posts). The combined recall and precision across these categories were 78.7% and 66.2%, respectively (calculated from [40], Tab. 4). Their completeness was approximately 5–10 percentage points higher than in PI and PIII, while correctness was 15–20 percentage points lower. If the same weight is put for the precision and the recall, the mean accuracies (PI, Eq. 2) in PI and PIII would have been approximately 5–7 percentage points higher compared to Golovinskiy et al. [40]. Hofmann and Brenner [48] achieved a correctness of 94% in the pole detection, which is approximately 10 percentage points higher than in PIII. However, they did not report the completeness of the detection. Because a trade-off almost always exists between completeness and correctness, it is difficult to perform a comparison. Therefore, based on the above comparison, the results of PI and PIII implied that the accuracy of polelike object detection could be slightly higher than had been reported in previous studies. The difference may be explained by the fact that the aim of Golovinskiy et al. [40] was general object recognition, and they did not focus specifically on polelike objects. The selection of the five polelike object categories of Golovinskiy et al. above was based on my interpretation and may contain uncertainty. Moreover, Golovinskiy et al. used a combined MLS–ALS dataset whose local relative 3D error was approximately 5 cm or higher, while in PIII, the local accuracy of the point cloud was better than 1 cm.

On the methodological side, the pole detection algorithm reported in PI (Algorithm 1) may have improved the generality, efficiency, accuracy, or practicality of the automated polelike object detection compared with the methods published before it [25, 20, 92, 40]. First, Algorithm 1 contained no restrictions to the locations of the poles except for the maximum allowed distance from the trajectory (eg poles do not need to be located in front of buildings). Second, the poles that were part of a larger object caused no problems, and each pole in an object was detected separately. Objects that contain two or more poles can be difficult for methods that rely on connectedness in the segmentation phase and do not
try to find polelike shapes. Compared to Brenner [20], Algorithm 1 applied a similar cylinder mask idea but utilised the point cloud’s scan line structure. The application of the scan line segmentation hastened data processing, because the searches were only performed at the neighbouring points along the scan line or at the neighbouring scan lines. Of course, the use of the scan line information reduces the generality of Algorithm 1 compared to methods that process unstructured point clouds (eg IV), as discussed above. Moreover, Algorithm 1 did not use machine learning. Learning methods as, for example, the ones applied in [40] may suffer from overfitting, and they often require the collection of training data when applied to new datasets.

Cabo et al. [21] generalised Algorithm 1. Like Algorithm 1, their algorithm was able to separate poles attached to the same object, but the input to the method was an unstructured point cloud. They therefore did not need the scanner’s scan line information. To achieve this, they applied voxels.

Algorithm 1 has also been applied by Puttonen et al. [104], and some parts of it in PV. In [104], Algorithm 1 was one of the three methods that were used to test how point cloud sub-sampling affects the performance of processing algorithms.

Since PI, the detection of polelike objects from MLS point clouds has been studied in more than 30 papers; see, for example, [142, 101, 21, 147, 145, 110, 148, 34, 125, 81, 152, 54, 138, 150, 153, 143, 140, 37, 137, 41, 76, 151, 33, 77, 57, 19, 11, 97, 127, 144, 109]. In several studies, both the recall and the precision of the detection have exceeded 90% [21, 147, 145, 110, 125, 81, 152, 138]. There are three reasons for the increase of the detection accuracy compared to PI and PIII. First, the quality and the density of the MLS point clouds have increased considerably (Figs 5.1 and 5.2). If the point measurement rate (PMR) in PI and PIII was 120 kHz, more than a million points per second have been collected in later studies [21, 147, 145, 152] when the use of more than one laser scanner

![Figure 5.1. A polelike object (part of it close to the ground) from the dataset of I. The mirror frequency was 15 Hz. Image from I.](image-url)
in the system is taking into account. Moreover, the frequency of the scanner’s mirror is currently almost ten times larger than in PI and PIII. While in PI and PIII the mirror frequencies were 15 Hz and 30 Hz, respectively, for example, in [21], the mirror rotated at a frequency of 200 Hz. Therefore, gaps that are almost ten times smaller remain between consecutive profiles, and consequently, ten times more sweeps are retrieved from single poles (Figs 5.1 and 5.2). Of course, driving speed is as important as mirror frequency and the PMR when considering the point density and its homogeneity. However, as most pole detection studies have concentrated on urban or suburban environments, driving speeds have been limited. Based on the current standards, the MLS point cloud at test site C (III) was considered sparse and unevenly distributed by Li et al. [76]. Moreover, the point density was even less homogeneous in the MLS data of PI, because the mirror frequency was as low as 15 Hz.

Based on a visual check of the point cloud at test site C, approximately a quarter of the missed targets had a low number of hits in the point cloud, and could probably be detected using the newest MLS systems with a higher PMR and mirror frequency.

Second, developments in the algorithms may have increased the accuracy of the pole detection. For example, most of the false positives were caused by building structures at test site C in PIII, and some were clearly above ground level. These could be removed by using building or ground extraction methods, as was done

Figure 5.2. A traffic sign in a 3D point cloud collected using the Roamer R4DW terrestrial mobile laser scanning system in 2019. The system contains Riegl miniVUX-1UAV and Riegl VUX-1HA scanners whose mirror frequencies are 100 Hz and 250 Hz, respectively. Their combined pulse repetition rate is 1.1 million pulses per second. Image by Antero Kukko.
in several later pole detection studies [147, 145, 110, 125, 81, 152, 138, 76].

Third, the differences in the test areas cause variability in the accuracies across studies, and test site C of this thesis proved challenging. The site contained a considerable number of trees whose polelike trunk was short and thick, or had vegetation (e.g., branches, bushes, or other trees) around them. The trees were therefore difficult to detect as polelike objects by the algorithm. They accounted for approximately 40% of the missed targets. Pu et al. [101] also faced difficulties in the detection of trees in the same Espoonlahti test area and data. Many targets were also close to other structures that prevented detection.

If the omission errors caused by the difficult trees and objects with a low point density were ignored, Algorithm 1 could probably reach a completeness of close to 90% or even higher at test site C. If the false detections from the buildings were ignored, the correctness value would be approximately 95%. These accuracies would be comparable to the current state of the art.

5.2.2 Research question 2: Is it possible to improve the accuracy of machine-learning-based object recognition from MLS point clouds in a road environment by using classification features that are based on the distribution of local descriptors, and what is the quality of the results?

The results of PIV suggested that segment classification accuracy could be increased by using classification features that described the distribution of local pointwise descriptors. Publication IV reported an increase of 9.6 percentage points for the classification accuracy when using local descriptor histograms (LDHs) compared to a state-of-the-art accuracy of 78.3%. The state-of-the-art features were general shape and point distribution features. To the best of my knowledge, PIV was the first study in which LDHs were applied in object classification in MLS data for surveying applications. Before PIV, LDHs had been applied in the point cloud segment classification in autonomous driving and general point cloud processing. See more details in PIV, Section I.

To understand the theoretical implications of PIV, some other point cloud classification methods are next reviewed with some approaches that others have used to tackle the issues found in PIV.

After PIV, Yang et al. [146] developed new features for point cloud segment classification in a highway environment, comparing their algorithm with the workflow developed in PIV. They aggregated features at point, segment, and object levels together, and added contextual features to classify the objects. A comparison with the workflow of PIV suggested that the new contextual and aggregated features outperformed those applied in PIV by 4.7 (precision) and 3.7 (recall) percentage points. However, it should be noted that the method of [146] was applied in a highway environment, whereas the PIV test area was in the suburbs.

Concerning classification features, Yang et al. [147] classified point cloud segments, using semantic rules. They achieved an overall accuracy of more
than 91%, which showed that non-learning methods could also achieve a high accuracy. The challenge in practical applications may be that new rules need to be developed in new environments – a difficulty similar to that in machine learning, where new training data are usually needed in new areas. In addition to the geometry, radiometric information may provide features that are useful in object recognition [123, 138]. For example, Soilán et al. [123] utilised retro-reflective properties of traffic sign boards to separate them from other vertical objects. They fitted a two-component Gaussian mixture model to the intensity distribution, thus separating the retro-reflective surfaces from other surfaces. The neighbourhood size of the local descriptors can be optimised [136], or perhaps local descriptors could be extracted and aggregated using several neighbourhood sizes.

In relation to classification strategies, Wu et al. [138] applied features at different levels of segmentation in a binary classification task. They achieved more than 95% precision and recall in lamppost recognition, using MLS point clouds. Yu et al. [150, 152] and Wang et al. [134] used template matching with feature points, bag-of-visual-phrases descriptors, and SigVox descriptors, respectively, to classify MLS point cloud segments. An advantage of these methods compared with machine learning is that in template matching, the user only needs to pick one example from each class instead of a training dataset of probably hundreds or thousands of examples. However, the use of only one example per class raises a concern about how sensitive the classification result is to the selection: how this approach can deal with intraclass variation in both object properties (e.g., shape) and data quality (e.g., occlusion). Golovinskiy et al. [40] suggested to aggregate features extracted using several segmentation methods. If combined with variable selection [44], the approach could diminish sensitivity to segmentation errors. Practical drawbacks of the approach may be heavier computation and the need to implement several algorithms.

In PIV, most of the object recognition errors were caused by undersegmentation when applying connected-component segmentation, that is, adjacent objects were attached to each other (e.g., a traffic sign was partly inside the tree branches). This issue – related especially to urban and suburban environments – has also been reported in [134, 152, 146, 132]. Yang and Dong [145] and Yang et al. [147] developed more sophisticated segmentation algorithms that resulted in more than 90% overall accuracies in an urban object extraction. They approached the undersegmentation problem by first oversegmenting the point cloud and then merging the segments, using graph-based algorithms, such as normalised cuts. In addition, they utilised shape (e.g., local planarity and surface normal) and colour or intensity features in the segmentation. Finally, the segments were combined in whole objects, using semantic rules. Yu et al. [150, 152] also achieved good segmentation results, using large datasets in an urban environment which contained a lot of vegetation. Their strategy was the opposite of the one in [147], because they first applied connected-component segmentation, which resulted in undersegmentation in many cases. They then improved the segmentation,
using the normalised cuts, which also utilised the intensity information in [152] to separate objects attached to each other. Detection recalls and precisions of more than 94% showed that the segmentation method worked well, and the undersegmentation caused few errors. However, a question remains concerning how they detected segments that contained two or more objects, and which were processed using the normalised cuts. Serna and Marcotegui [119] first detected objects as local maxima in the elevation image and then segmented the objects, using the watershed. Wu et al. [138] developed a rule-based segmentation method for lampposts that resulted in more than 95% precision and recall in the object recognition in datasets with a considerable amount of occlusion. A more detailed semantic segmentation of polelike objects and their attachments was performed by Li et al. [77, 78]. First, they segmented the object into components, such as a pole and its attached signs, based on spatial relations [77]. They then classified the attachments using machine learning and features describing the size, shape, radiometry, and context [78]. They achieved classification accuracies between 80% and 95%, using a random forest classifier.

The comparison with previous studies in PIV, Section IV-E indicated that the object recognition workflow reported in PIV could achieve similar accuracy to the other object recognition methods if a more sophisticated segmentation method was used. Trees especially suffered from undersegmentation at test site D, resulting in a recall of approximately 50%. As already mentioned, tree detection was also challenging for Pu et al. [101] in the same area and data. As discussed above, Yang et al. [146] compared their workflow to that of PIV and Yang et al. [147] in a highway setting. The workflow of PIV performed better than the method of [147], but worse than the method of [146]. The recall of the tree detection using the workflow of PIV was 84% in [146], which is more than 34 percentage points higher than in PIV. With the results of Pu et al. [101], this underlines the difficulty of detecting trees at test site D.

The comparison with previous studies in PIV indicated some differences between autonomous driving and surveying applications, the latter being the focus of this thesis. Chen et al. [24] studied the classification of point clouds provided by an autonomous vehicle. They found that the spin images outperformed the LDHs in segment classification, whereas the situation was the opposite in PIV. In [24], the dimensionality of the LDH feature vectors was significantly lower than in PIV, which probably caused the lower classification accuracy of LDHs in [24]. The reason for using a lower dimensional feature vector in [24] was probably that the classification needed to be performed in real time in their application.

PIV’s results have also been utilised in other studies and research projects. The classification results of PIV were used as a reference in [74], in which a preregistration classification method for MLS was studied. A planar patch extraction method reported in the study of Zhu et al. [154] used the voxel-based point cloud processing tool that was originally developed for MLS data in PIV. In the NavDrive project [9], the workflow of PIV was tested using Velodyne-
based point clouds at test site D. The ground and building extraction methods developed in PIV have also been tested in an industrial area in Kokkola, Finland.

5.2.3 Research question 3: How completely can power lines be detected from MLS point clouds outside the road network, and what is the quality of the results?

To the best of the author’s knowledge, at the time of publication, PV was the first study of MLS power line detection outside the road network. To account for the difficulties in the mapping of the power lines in forested areas (PV, Sec. 3.2), larger tolerances probably had to be applied in the parameters of Algorithm 3 than in the previous MLS power line studies, all of which were conducted in suburban and road environments [141, 42, 27, 63, 139]. For example, the maximum normal distance from the line in RANSAC was as high as 10 cm in PV, whereas a significantly smaller value could probably be used in a road environment. As a result of using larger tolerances, more false detections were found, the amount of which further increased due to the large number of false power line candidates found in the forest. To reduce the number of false detections, the CPLS method was developed in PV, Sec. 4.3.1.

The accuracy of the power line detection in PV was comparable to the accuracies reported in previous MLS-based power line studies when the differences between the urban and rural environments were taken into account (V, Sec. 5.6.4.). This also applies to the study of Xu and Wang [139], who were not cited in PV due to the proximity of publication dates. All previous power line studies using MLS focused on suburban or road environments. However, PV focused on areas outside the road network (forest and farmland). Outside the road environment, especially in the forest, the drifting of positioning and the inhomogeneous point density caused problems that were the main cause of the differences in the power line detection accuracies between previous studies and PV.

Recently, Jung et al. [59] conducted a thorough study of automated power line detection in a road environment, using mobile and static terrestrial laser scanning. They tested their power line detection algorithm on 30 sites, with various site characteristics, and performed a thorough parameter sensitivity analysis. Their algorithm was fast compared to previous algorithms, and did not require any supplemental information, such as vehicle trajectory.

5.3 Practical implications

This section describes the kind of practical implications the results of this thesis could have. The object recognition accuracies reported in this thesis demonstrate the potential of MLS in corridor mapping. This information may boost the application of MLS technology. For example, the road authorities may recognise the potential of MLS to enhance the efficiency of the inventory of
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roadside objects, such as traffic signs and lampposts.

In this dissertation, the difficulties of the automated processing of MLS point clouds are analysed. For example, the thesis contains analyses of both the commission and omission errors (the precision and the recall) and their causes. The error analyses will assist practitioners in understanding the limitations of MLS technology and automated point cloud interpretation.

The size of the global lidar market was approximately between USD 0.5 and 2 billion during 2017 and 2018 [7, 6, 5, 8], and based on various estimates, between 2023 and 2025, it will be between USD 1.8 and more than USD 10 billion [6, 5, 1, 8, 4]. In addition, the size of the global TLS market is expected to be USD 2.5 billion in 2023 [3]. The global lidar market will therefore probably increase significantly in coming years, and lidar-related research – including mobile terrestrial laser scanning – will therefore also have a practical impact.

In Finland, the inventory of road defects costs between 50 and 100 euros per kilometre, depending on the level of detail and accuracy of information needed. The Finnish state owns 78,000 km of road, and annual road defect inventory costs are approximately one million euros. Currently, the inventory of defects is performed manually, and the accuracy is approximately 80%. Manual inspection is prone to subjective interpretation. The desired accuracy of the automated methods would be 95%–98%. If the inventory was automated, using mapping sensors such as laser scanners, it is expected that savings of half a million euros could be achieved annually. Furthermore, as the quality of information increases due to more detailed, accurate, and objective mapping methods, the information can be better utilised to improve road environment mapping and maintenance in general (not only defects). This could result in savings of tens of millions of euros in road maintenance in Finland annually. This thesis demonstrates that automated interpretation of MLS data is possible. The thesis also contains advances in point cloud algorithm development. These may help to achieve the desired accuracy, efficiency, and objectivity in road maintenance, and therefore create savings for society in future. The Finnish infrastructure and construction service company Destia has started to use MLS in road environment mapping. Destia has also shown interest in point cloud algorithms to process MLS data more efficiently.

When considering the practical applicability of MLS or any other mapping technology, it is not only the performance of the processing algorithms but the visibility of the objects in the data that is important [135]. The algorithms are typically evaluated against the data reference (I, III), that is, the reference that contains all objects identifiable in the point cloud by a human operator. However, if the objects cannot be identified from the point cloud even by a manual inspection, the technology is not useful. In PI and PIII, the visibility of polelike objects in the MLS point clouds was analysed in a road environment. At test sites A and C of PI and PIII, respectively, approximately 86% and 74%, respectively, of the polelike objects found in the field could be identified in the point cloud by a human observer. A modest number of other visibility studies
has been conducted for MLS point clouds in a road environment. Cabo et al. [21] found that almost all objects found in the field could be identified from the point cloud. The width of their test area in the direction perpendicular to the driving direction was approximately 80 m, and occlusion was not a major issue. The main reason for the differences between the results of this thesis and those of [21] is probably that the point density was almost ten times higher in [21] compared to test sites A and C. In addition, the more homogeneous point density due to the higher scanning frequency and lower level of occlusion in [21] compared with sites A and C probably had an impact.

Annually, USD 169 billion is lost globally in the power and utilities sector because of failures in the transmission and distribution of electric power [2]. In countries that are largely covered by forest (e.g., Finland), a large proportion of the power line corridors are also located in the forest. There, falling trees, crown snow-load, short circuits, and forest fires can cause power outages and other failures. The monitoring of the condition of power line corridors therefore has huge business potential. In PV, Sections 1 and 6, the potential of MLS for power line inspection was demonstrated and discussed. Publication V focused on a rural area outside the road network that included forest and farmland. The paper discussed the feasibility of MLS for cost-effective power line mapping – either alone or to support aerial inspection.

Autonomous driving will probably be one of the biggest changes in the world in the coming decades. Laser scanners will be one of the key sensors in autonomous vehicles [75, 118]. In addition, high-definition (HD) maps may be a fundamental part of autonomous driving in future, and MLS may be one of the key technologies for producing HD maps [118]. Data interpretation algorithms will be crucial when processing sensor data collected by autonomous vehicles, as well as when producing nationwide HD maps.

Mobile laser scanning with ALS could aid in map updating [130, 95]. Currently, 150–200 people (full-time workers) are needed to maintain Finland’s topographic database [130]. Considerable savings are expected when more automated procedures are developed for map updating, including point cloud interpretation algorithms.

Other fields which could benefit from MLS-based road corridor mapping and automated data interpretation algorithms are 3D city modelling, building information modelling, road and street planning, air and noise pollution modelling, location-based services, personal navigation, virtual and augmented reality, urban tree mapping [124], and road lighting modelling [128].

5.4 Recommendations for future research

The algorithms developed in this thesis contain several parameters and thresholds. When the algorithms are applied to new datasets and test sites, the parameters are typically tuned for optimal performance. It would be beneficial
if the sensitivity of the methods for each parameter were known beforehand. One might then be able to pick control parameters, as suggested by Lehtola et al. [74], tune them, and leave the rest of the parameters untouched. This would make the methods more feasible for practical applications. The sensitivity analysis of parameters and the classification of control parameters will therefore be an important topic of future study.

The machine-learning methods applied in PIV typically need training when applied to new unseen data. This requires the collection of training data, which may be laborious. Image-based tools could be developed to collect the training data more efficiently and reliably.

The classification of point cloud segments in PIV could be improved by removing the heterogeneous ‘undefined’ class, which caused a considerable number of errors (IV, Sec. IV-F). Instead, one can use methods that provide a reliability measure as, for example, the posterior probability [108] for each class to remove objects that are not of interest or to alert the user when an undefined object is observed. Like the reliability measure, a quality flag indicating how well the automated interpretation has worked [88] would be useful in practical applications.

The density of MLS point clouds has increased considerably during the writing of this dissertation and may continue to increase due to advances in single-photon techniques [14], for example. More detailed information can therefore be extracted from the data, and it may be possible, for example, to detect and measure the small cracks and holes on the road surface, as well as road surface rutting, using MLS at normal driving speeds in road environments. In addition, using more than one wavelength [60, 39, 95, 149] may improve detection and classification accuracies.

In power line corridors, the next natural step would be to measure the distance between the power lines and the surrounding vegetation. MLS provides dense and accurate data below the canopy. In future, it may be possible to increase the accuracy of ALS-based prediction models for vegetation growth by also utilising dense MLS point clouds. This would allow for the more efficient maintenance of power line corridors. Here, bi- or multi-spectral laser scanners may also provide more accurate prediction models.

UAV-based power line inspection could be complemented by MLS data to map the power line components and the surrounding vegetation more thoroughly [87]. The efficiency of MLS in filling the gaps after an aerial power line inspection should also be studied to identify optimal approaches for efficient combined ALS–MLS inspection. As the positioning errors of the MLS reduced the power line mapping accuracies in PV, new approaches for location and attitude determination will be an important study topic. Such new approaches include SLAM – either as a post-processing approach [72] or as an additional 3D scanner instrumentation – the use of dense airborne point clouds as a positioning reference [94], and the use of a more accurate IMU. Point density was occasionally inhomogeneous in PV due to moving restrictions, which caused errors in power
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line detection. Sampling methods may be able to homogenise the density.

Deep learning, and especially deep convolutional neural networks, has gained state-of-the-art accuracies in many computer vision problems [116]. In addition, deep-learning-based methods have won many computer vision competitions and produced best results with several benchmarking datasets [28, 116, 29, 113]. Deep learning has also been applied to point cloud interpretation [38, 43] and has provided state-of-the-art results in point cloud classification, segmentation, and object detection [105]. A multitude of network structures can be constructed [43, 80] by varying data structures (e.g., points, graphs, octrees), and feature learning, convolution, and context approaches, for example. This has opened vast possibilities for model selection, and consequently, more than 60 [43] point-based network variants have been developed for 3D point clouds since 2015 that perform shape classification or semantic segmentation. Although mostly developed for small point clouds (e.g., less than ten thousand points) [43] and therefore not applicable to MLS data, deep learning has nevertheless been applied to the classification of MLS point clouds, see, for example, [80, 152, 23]. For instance, Yu et al. [152] successfully applied a deep Boltzmann machine to extract bag-of-visual-phrase features for detecting traffic signs. They achieved average recall and precision values of more than 94% with a test set of more than 1,300 traffic signs. Luo et al. [91] introduced a new data structure by slicing the point cloud along the vertical axis, and applying a recurrent sequential slice network (RSSNet). Their system also contained a key-point-based graph convolution network, which was fused with the sequential slice features, using attention embedding strategy. He et al. [46] studied how complementary training data from another area could increase MLS point cloud classification accuracy – also called transfer learning – using convolutional neural networks and a novel multi-class TrAdaBoost algorithm. Luo et al. [90] studied unsupervised scene adaptation for deep-learning-based semantic segmentation of MLS point clouds. In their approach, no new training data is needed when the method is applied to new scenes. In practice, the power of deep methods is probably based, for the most part, on their ability to learn better features (Sec. 2.3) from the data than what experts can invent for traditional ‘shallow’ models. Many MLS applications, including autonomous driving [80], will probably utilise deep learning in future.

Supervoxels [98] have become popular data structures in MLS point cloud processing in recent years [132, 138, 147]. Thus far, they have mostly been used to improve computational efficiency, which is important, because MLS systems collect large amounts of data. Supervoxels replace points or voxels as the elementary processing units. Supervoxels may also improve graph-based processing compared with segments retrieved using surface growing, because supervoxels are divided more uniformly in the space, and their size variation is small [98]. Supervoxels may also be more reliable processing units than single points due to their larger size (the number of points): for example, a larger size may reduce the noise in local descriptors.

The use of open data sources could increase the accuracy of data interpretation.
For example, errors in ground extraction reduced object recognition accuracy in PIV. The open nationwide airborne laser scanner data in Finland can probably provide digital elevation models when MLS data fail to cover the ground. During the next six years, Finland will be scanned again, using a higher density of five points per square metre. This data could be utilised to improve georeferencing accuracy in power line corridors, where GNSS signals may be blocked by tall trees.

The suburban test sites of this dissertation proved challenging. A prominent reason for the difficulties was the considerable amount of forest and hence trees that were attached to each other and surrounded by branches. As data quality has increased since the suburban studies of this thesis, more sophisticated algorithms such as those by Liang et al. [85] could be used today for tree extraction from MLS point clouds.
References


Errata

Publication IV

The abstract incorrectly claims that the improvement in the classification accuracy is 9.6%. The correct improvement is 9.6 percentage points.