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TREE SPECIES CLASSIFICATION WITH MULTIPLE SOURCE REMOTE SENSING DATA

by

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Tree Species Classification with Multiple Source Remote Sensing Data

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Abstract

Remote sensing is a study that provides information on targets of interest without direct interaction with them. Generally, the term is used for measurement techniques that detect electro-magnetic radiation emitted or reflected from the targets.

Commonly used wavelength ranges include visible, infra-red, microwaves, and thermal bands. This information can be exploited to determine the structural and spectral properties of targets. Remote sensing techniques are typically utilized in mapping solutions, environment monitoring, target recognition, change detection, and in creation of physical models.

In Finland, remote sensing research is of specific importance in forest sciences and industry as they need precise information on tree quantity and quality over large forest ranges. Tree species information on individual tree level is an important parameter to achieve this goal.

The aim of this thesis is to study how individual tree species information can be extracted with multiple source remote sensing data. The aim is achieved by combining spatial and spectral remote sensing data. Structural properties of individual trees are determined from three dimensional point clouds collected with laser scanners. Spectral properties of trees are collected with cameras or spectrometers.

The thesis consists of four separate studies. The first study examined how shading information of trees canopies could be exploited to improve tree species classification in data collected with airborne sensors. The second study examined the classification performance of a low-cost, multi-sensor, mobile mapping system. The third study investigated the classification performance and accuracy of a novel, active hyperspectral laser scanner. Finally, the fourth study evaluated the suitability of artificial surfaces as on-site intensity calibration targets.

The results of the three classification studies showed that the use of combined point cloud and spectral information yielded the best classification results in all study cases when compared against classification results obtained with only structural or spectral information. Moreover, the studies showed that the improved results could be achieved with a low total number of mixed structural and spectral classification parameters. The fourth study showed that the artificial surfaces work as calibration surfaces only in limited cases.

The main outcome of the thesis was that the active remote sensing systems mea-

suring multiple wavelengths simultaneously should be promoted. They have a significant potential to improve tree species classification performance even with a few application-specific wavelengths.

Keywords: Remote Sensing, Laser Scanning, Spectral Imaging, Tree Species Classification, Data Fusion

Abstrakti

Kaukokartoitus on tutkimusala, jossa tutkittavia kohteita havainnoidaan ilman suoraa vuorovaikutusta. Yleisimmin kaukokartoituksella tarkoitetaan mittaustekniikoita, joilla havaitaan kohteiden lähettämää tai heijastamaa elektromagneettista säteilyä.

Havainnointi tapahtuu tavallisesti näkyvän valon, infrapunan, mikroaaltojen ja lämpösäteilyn aallonpituusalueilla. Havaittua säteilyä voidaan hyödyntää kohteiden rakenteellisten ja spektraalisten ominaisuuksien määrittämisessä. Kaukokartoitusmenetelmiä käytetään tyypillisesti kartoitussovelluksissa, ympäristönseurannassa, kohde- ja muutostulkinnassa sekä fysikaalisten ilmiöiden mallinnuksessa.

Kaukokartoitustutkimuksella on tärkeä osa suomalaisessa metsäntutkimuksessa ja -teollisuudessa. Molemmat tarvitsevat tarkkaa tietoa puuston määrästä ja laadusta suurilta metsäalueilta. Yksittäisten puiden lajitulkinta on tärkeä parametri tavoitteen saavuttamisessa.

Väitöskirjatutkimuksen tarkoituksena on selvittää, kuinka yksittäisten puiden lajitieto voidaan määrittää eri mittauslaitteilla kerätystä kaukokartoitusaineistosta käyttämällä samanaikaisesti puustoa kuvaavia muotopiirteitä ja spektrivastetta. Muotopiirteiden keräys tehdään laserkeilaimilla. Spektrivasteet kerätään kameroilla tai spektrometreillä.

Väitöskirjan sisältö koostuu neljästä erillisestä tutkimuksesta. Ensimmäisessä tutkimuksessa selvitetään, kuinka ilmasta kerättyä tietoa puiden latvustojen varjostumisesta voidaan hyödyntää puulajitulkinnassa. Toisessa tutkimuksessa arvioidaan puulajitulkinnan toteutettavuutta aineistosta, joka on kerätty edullisista komponenteista kootulla liikkuvalla kaukokartoituslaitteistolla. Kolmas tutkimus tarkastelee uuden, aktiivisesti mittaavan hyperspektrilaserin suorituskykyä ja tarkkuutta puulajitulkinnassa. Neljännessä tutkimuksessa selvitetään voidaanko rakennettuja pintoja hyödyntää intensiteetin maastokalibrointikohteina.

Kaikki kolme luokittelututkimusta osoittivat yhdistetyn pistepilvi- ja spektriaineiston suoriutuvan parhaimmin lajitulkinnasta, kun tuloksia verrataan pelkästä rakenne- tai spektrisestä aineistosta laskettuihin tuloksiin. Lisäksi parantuneet tulokset saavuttiin yhdistämällä vain muutamaa rakenne- ja spektri-luokitteluparametria kerrallaan. Neljännen tutkimuksen tulokset osoittivat, että rakennetut pinnat soveltuvat kalibraatiokohteiksi vain rajatuissa tapauksissa.

Väitöskirjan tärkein johtopäätös on, että aktiivisten, useaa aallonpituutta samanaikaisesti mittaavien kaukokartoituslaitteistojen kehitystä tulisi edistää. Tällaiset laitteistot voisivat parantaa puuston lajitulkintaa huomattavasti jo muutamaa sovellukseen sopivinta aallonpituutta käyttämällä.

Avainsanat: Kaukokartoitus, Laserkeilaus, Spektrikuvantaminen, Puulajitulkinta, Datafuusio

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Writing this thesis has been a long journey spanning over several years, and it would not have been possible without the help, commentary, and contribution of other people.

I would like to thank prof. Hannu Koskinen for accepting to act as a custos for the defense of my dissertation. I am also grateful for the teaching I received years ago in undergraduate courses about electrodynamics. They gave me a strong background to understand the physical basis of remote sensing.

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My other supervisors, Jouni Peltoniemi and Sanna Kaasalainen, have also given me a great opportunity to understand remote sensing by letting me to work in their projects which has helped me to see how different problems can be approached in several ways. My gratitude goes also to you. I also want to thank Jouni for first introducing me to the FGI in 2006. The first summer at the Finnish Geodetic Institute with all its measurement campaigns is something I still remember with warmth.

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The Finnish Geodetic Institute has offered a good working environment for me over the years. While it has provided me with the equipment and infrastructure needed for conducting my studies, it also provides and supports recreational activities of its employees in various forms for which I am very thankful.

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Finally, my sincere thanks go to my family and friends who have always given me their support and helped me to move my thoughts from work and studies.

Kirkkonummi, June, 2012
Eetu Puttonen

List of abbreviations

AISA	Airborne Imaging Spectrometer Array
ALS	Airborne Laser Scanning/Scanner
ALTM	Airborne Laser Terrain Mapper
AM	Amplitude-Modulation
ASD	Analytical Spectral Devices
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVIRIS	Airborne Visible/InfraRed Imaging Spectrometer
BRDF	Bidirectional Reflectance Distribution Function
BRF	Bidirectional Reflectance Factor
CASI	Compact Airborne Spectrographic Imager
CHM	Canopy Height Model
CIR	Colour-InfraRed
DBH	Diameter at Breast Height
DMC	Digital Mapping Camera
DSM	Digital Surface Model
DTM	Digital Terrain Model
ESA	European Space Agency
EuroSDR	European Spatial Data Research
FGI	Finnish Geodetic Institute
FIGIFIGO	Finnish Geodetic Institute Field Goniospectrometer
FOV	Field of Vision
FWHM	Full-Width at Half-Maximum
GPS	Global Positioning System
GSD	Ground Sampling Distance
HDRF	Hemispherical-Directional Reflectance Function
IMU	Inertial Measurement Unit
LDA	Linear Discrimainant Analysis
LiDAR	Light Detection and Ranging
MERIS	Medium Resolution Imaging Spectrometer
MLS	Mobile Laser Scanning/Scanner
MODIS	Moderate-resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Agency
nDSM	Normalized Digital Surface Model
NIR	Near-Infrared
RADAR	Radio Detection and Ranging
RBF	Radial Basis Function
SAR	Synthetic Aperture Radar
SONAR	Sonic detection and Ranging
SPOT	Systéme Probatoire d'Observation de la Terre
SVM	Support Vector Machine
TLS	Terrestrial Laser Scanning/Scanner

Publications

I Puttonen, E., Litkey, P., Hyyppä, J., 2009. Individual tree species classification by Illuminated-Shaded area separation. Remote Sensing 2 (1), 19-35, DOI: 10.3390/rs2010019

II Puttonen, E., Jaakkola, A., Litkey, P., Hyyppä, J., 2011. Tree Classification with Fused Mobile Laser Scanning and Hyperspectral Data. Sensors 11 (5), 5158-5182, DOI: 10.3390/s110505158

III Puttonen, E., Suomalainen, J., Hakala, T., Räikkönen, E., Kaartinen, H., Kaasalainen, S., Litkey, P., 2010. Tree species classification from fused active hyperspectral reflectance and LIDAR measurements. Forest Ecology and Management 260 (10), 1843-1852, DOI: 10.1016/j.foreco.2010.08.031.

IV Puttonen, E., Suomalainen, J., Hakala, T., Peltoniemi, J., July 2009. Measurement of Reflectance Properties of Asphalt Surfaces and Their Usability as Reference Targets for Aerial Photos. IEEE Transactions on Geoscience and Remote Sensing 47 (7), 2330-2339, DOI: 10.1109/TGRS.2008.2010132

I am the main author of all studies in this dissertation with contributions from all co-authors. I also did the data analysis and data processing needed for analysis in all studies. Additionally, I performed data fusion in studies **I** and **II**, and took part in the measurements in the study **IV**. Also, I arranged tree species samples in the study **III**.

Contents

Chapter 1

Introduction

1.1 Foreword about Remote Sensing

1.1.1 Remote sensing

Remote sensing can be defined as 'the acquisition of information about an object or phenomenon, without making physical contact with the object' [1]. This definition covers a wide range of scientific methods and techniques. However, the concept of remote sensing has also a very palpable meaning as several human senses utilize it to give us information about our surroundings: our eyes detect electromagnetic radiation at wavelengths different from those which form the image of the surroundings, our skin senses infrared waves, and our ears detect changes in pressure. While the term remote sensing can be used in a very broad context, in general it means the detection of electromagnetic radiation being emitted or scattered from objects observed on our planet. Also, acoustic and seismic waves have been exploited for a long time in various applications in maritime and earth sciences.

Remote sensing studies, in the modern sense of the term, began with the invention of the camera (*camera obscura*) in the 19th century. Cameras were attached soon in balloons and airplanes to provide information on the features at the ground level as seen from above. But it took until the beginning of the 20th century before large scale use of remote sensing data began. Remote sensing data were especially needed for intelligence gathering during World War I. Overall, the development of remote sensing techniques has been closely linked to military applications as most of the new methods and equipment were first applied for intelligence purposes and then became gradually more and more usable for the scientific community and commercial enterprises. Techniques such as SOnic Navigation And Ranging (SONAR), RAdio Detection And Ranging (RADAR), and various satellite systems were all first used in military surveillance. The latest remote sensing technique, LiDAR (Light Detection And Ranging), was also introduced first in military applications such as artillery ranging tasks.

1.1.2 Remote sensing data, data collection, and domains

The data collection methods used with remote sensing measurement systems may be divided into two main categories, passive and active. Passive remote sensing systems measure target areas and objects that are either self-emitting (e.g. hot objects in long wavelength infra-red) or are illuminated by an external light source. This introduces severe limitations to their usability because additional efforts are needed to monitor and correct possible changes in the incoming illumination. However, when good measurement conditions and proper calibration are provided, passive remote sensing systems are capable of collecting large amounts of data with a high degree of accuracy. Moreover, passive remote sensing systems collect data with a high degree of detail.

Active remote sensing systems both send and receive signals. This makes them independent of external conditions. In addition, data calibration in an active measurement is significantly more straightforward than in passive measurements because both the transmitter and the measurement calibrations can be carried out independently without mixed response. Furthermore, the travel time of a transmitted signal can be detected with a high degree of accuracy thus enabling precise ranging. At present, the most common applications of active measurement systems are related to ranging and mapping of objects and areas of interest. One of the main limitations of active remote sensing systems is that they are usually limited to operating on narrow transmitter bands. In optical remote sensing systems, this means using only one or a few separate wavelengths at a time. This limitation is due to the technical challenges that make it difficult to produce an actively measuring optical system that would be capable of producing both stable and coherent signals on several different wavelengths for radiometric measurements [2]. Another limitation with the present active optical systems is that the signal-to-noise ratios needed for precise radiometric measurements require total transmitting power exceeding the imposed safety regulations when several wavelengths or wavelength bands are applied.

Remote sensing data yields information about the target object's shape, reflectance spectrum, or both, depending on the data collection technique used. Thus, remote sensing data are suitable for creating accurate target models. The creation of a complete target model requires that the collected remote sensing data are required to fulfill both the model-specific resolution and coverage requirements. These requirements depend on the complexity of the modelled system. Natural object modeling is an especially complicated task as these objects are complex in structure. The remote sensing data obtained from living objects of the same species usually show significant variance in size, in their spectral and radiometric responses, and they change over time. The achievable object model accuracy depends on the type of available remote sensing data, data resolution, and data coverage.

Both data resolution and coverage have multiple meanings in remote sensing as remote sensing data collection is performed in several different domains, i.e. spatial, spectral, radiometric, and temporal. The data resolution and coverage in each of the domains are sensor-specific. Typically, one sensor is built to be capable of high performance in one or two domains at time. Thus, it is often necessary to fuse data from different remote sensing sensors to form the complete object model. The spatial characteristics of targets, such as their shape and geometry, can be derived either from LiDAR point cloud data, from imagery with photogrammetric methods, or from Synthetic Aperture Radar (SAR) data. Targets can be also separated from their surroundings for further processing using their spectral responses. All objects reflect, absorb, and transmit electromagnetic waves in an intrisic manner depending, to some extent, on their material and structure. The components of reflected waves are observed as a target-specific spectrum. The detected spectrum is not only dependent on the target properties; it also depends on the spectral shape of the incident illumination or of the signal hitting the target and on the measurement geometry. Target spectra are collected using cameras or spectrometers. More recently, innovative laser systems enable the concurrent transmission and collection of data over several wavelengths.

The spatial accuracy of remote sensing data is described in terms of resolution; this indicates the size of the smallest detectable object in the data. With LiDAR data, spatial accuracy is often reported either as the smallest detectable distance between two points or as the average point spacing in the data. Average point spacing is used because point cloud resolution depends significantly on the scanning geometry. This leads to distinct variation in individual point spacing. In imagery, the spatial resolution is usually reported as the ground sampling distance (GSD), which indicates the projected size of a single pixel at ground level. With a single detector, where the sensor records returning signals consecutively, the spatial resolution can be given as the spot size on the ground or on a target. The spatial resolution of a sensor system can be also reported as the divergence angle of the sensor field of vision (FOV), and the spot size can be derived from this when the distance to the scatterer is known. Figure 1.1 illustrates the concepts of spatial resolution and coverage.

Spectral accuracy is dependent on several sensor properties. The first property is the spectral resolution which determines how narrow individual wavelength components of the spectrum can be and still be distinguishable. At the sensor level, distinguishability means the smallest detectable wavelength difference be-

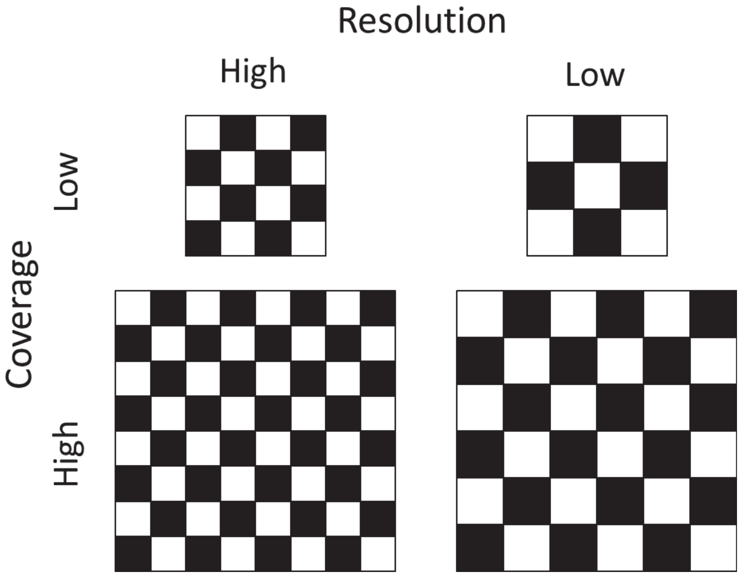

Figure 1.1: The concepts of spatial resolution and coverage illustrated using checkerboards. The horizontal direction represents the difference in spatial resolution. Checkerboards with small squares have a higher resolution than the boards with large squares. The vertical direction represents the difference in spatial coverage. The small checkerboards in the upper row cover less area than the large checkerboards in the lower row.

tween two sensor channels. The spectral resolution of a sensor is usually reported as the full-width-at-half-maximum (FWHM) which can be compared against the channel number and spacing of the sensor to see whether or not neighboring sensor channels overlap. Spectral information is mainly collected using spectrometers whose spectral channels are very narrow, ranging from one to a few nanometers whereas the spectral channel of a pan-chromatic camera can be several hundred nanometers wide, and with imaging systems, such as cameras, whose spectral channels can be hundreds of nanometers wide. The second important sensor property in spectral measurements is its radiometric resolution. Radiometric resolution determines, in physical terms, how sensitive a sensor is to incoming radiance. In practice, radiometric resolution indicates how small an intensity level changes a sensor can detect from a recorded signal. In imaging, the viewer sees high radiometric resolution as an overall smoothness of color changes and shades, or the ’color depth’, in the image. Figure 1.2 illustrates the concepts of spectral resolution and range.

Temporal resolution tells the shortest time interval after which data collection

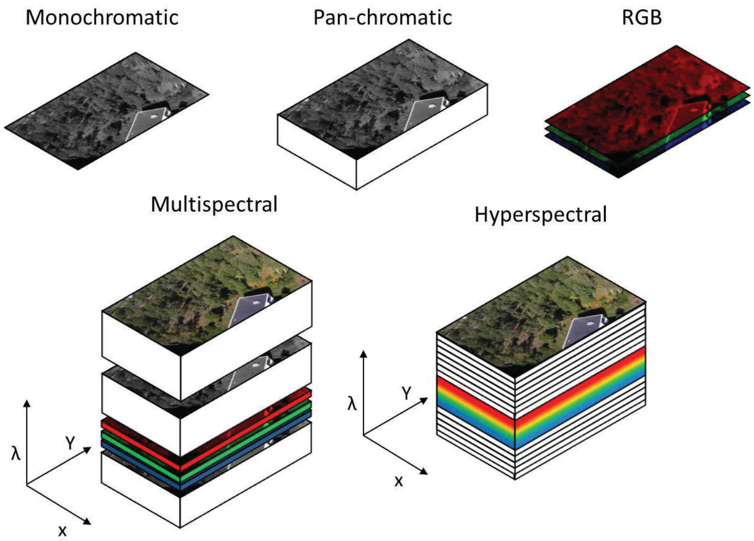

Figure 1.2: The concepts of spectral resolution and range where (x,y) plane describes the spatial domain i.e. image area, and λ describes the spectral domain i.e the covered wavelength range. The subfigures show the general differences between the various types of spectral data. Each layer in the spectral domain represents a single spectral channel or band. The thickness of the spectral layers represents the resolution of the detected channels and bands. The thin layers represent high spectral resolution and wide layers represent low spectral resolution. The total height of the spectral channels and bands represents the wavelength range covered by the sensor.

from the target of interest can be repeated. For example, camera systems are able to record several images images per second whereas satellite platforms may need to circle the Earth for weeks or months before passing over the same target area again. However, defining the temporal resolution of measurement is not always straightforward: the fastest LiDAR scanners can record hundreds of thousands of laser points per second, but the collecting of a complete point cloud around a scanner may take several minutes.

The second important characteristic that describes remote sensing data is data coverage. It tells how extensively the data is collected in each of the four domains. In the spatial domain, the coverage is the total area of the collected data. It can extend from some square meters to hundreds of square kilometers depending on the platform used. In the spectral domain, the coverage tells the total width of the recorded spectrum, be it collected in parts or as a whole. In the radiometric domain, the coverage defines the width between the lowest and the highest distinguishable reflectance levels. An incoming signal having a reflectance below the lower threshold remains undetected and a signal with reflectance above the higher threshold saturates the sensor. In the time domain, the coverage defines how long or how many times the target of interest is monitored over time.

In summary, information from the four separate domains, each having their own resolution and coverage, need to be considered when deciding how remote sensing data should be measured and processed for producing a complete object model. The maximization of resolution and coverage in all of the domains is not a practical, nor is it a feasible, solution, as it would mean that the measurement system's cost becomes unaffordable. Also, the amount of data processing and storaging would likely become unmanageable in such a situation.

1.1.3 Forestry research and forest inventory using remote sensing

In scientific research, accurate information from all of the previously introduced domains is needed in environmental monitoring, carbon sequestration, biomass estimation, and natural habitat mapping, to name a few fields of research. Also, information about on-going changes in growth conditions can be obtained. Non-scientific applications requiring accurate forest information include both industrial and non-industrial uses.

Forest industry needs remote sensing data for operational forest managing and planning of harvest operations. Globally, forest inventories were evaluated to be worth USD 2 billion in 2005. These inventories are being increasingly conducted using laser scanning instead of traditional standwise-field-inventory (SWFI) methods. As an example of this, approximately 5.5 million hectares of forests in Finland were scanned by different operators by the end of 2011. Area-based approach (ABA) is the most widely spread remote sensing inventory technique at the present. It was introduced at the end of the 1990's. ABA was first used in estimating mean heights and volumes of trees at the forest stand level.

Improvements in remote sensing techniques have enabled data collection focusing on individual trees. Individual tree detection (ITD) requires higher point densities than ABA, but it is estimated to bring timber assortment differentiation to a level where accurate stem distribution can be extracted directly from the data. In ABA, stem distributions need to be predicted, and this leads to increased inaccuracy in estimation. Moreover, ITD provides higher level of automation than ABA does, and thus it requires less field-based measurements. Moreover, ITD offers improved means of detecting suppressed trees in data.

Stem distribution data are important as they characterize the number and sizes of trees in the study area. However, these data alone are not enough for determining the tree species. If the tree species data were available, it would be possible to use the data with stem distribution data for high precision evaluations. Evaluations are essential for enabling improved modeling. Tree species classifications have been done using both laser scanning data and aerial imagery data, but both of these have their limitations. Laser scanning data are limited to very narrow wavelength band(s), and thus allow only minor additional classification capability in cases where the tree species cannot be discerned based on their shape. Imagery data contain information from a wider spectral coverage, but passive collection techniques mean that they are susceptible to changes in surrounding lighting conditions, the direction of lighting, and shadowing. It is possible to combine laser scanning and spectral imagery data, and then use fused datasets to determine tree species. The setback associated with using separate datasets is that data combination is computationally heavy and still retain some of the limitations of the individual methods.

All in all, the most optimal remote sensing data for individual tree species classification and stem size determination can be assumed to contain a spatial point cloud where each point carries its own, directionally corrected, spectral data. A promising way to produce these type of data could be innovative laser scanner systems that are capable of transmitting and detecting several different wavelengths, or perhaps even a continuous waveband, simultaneously. However, such systems are not available at present for operative use. This makes active, multi-wavelength, laser scanning a highly interesting research subject.

1.2 The Focus of the Present Dissertation

The scope of the present dissertation is to study how new data collection and combination techniques can be utilized in the classification of tree species. The tree species classification problem is approached from the viewpoint of individual trees. This imposes certain requirements on data resolution and data processing. The first data requirement is that the data need to have a spatial resolution that is high enough for determining the geometry of an individual tree. The second requirement is that the available spatial and spectral data, when combined, should provide enough information for differentiating tree species even within the same tree genus.

The requirements imposed on data processing are, to begin with, that the level of automatization should be as high as possible while retaining classification accuracy. Data processing should also be capable of distinguishing the most relevant features from the combined data. With efficient feature screening, the total processing costs are significantly reduced without a loss in overall classification accuracy. Furthermore, the data processing methods should be developed so that they would be usable regardless of the applied data collection methodology and timing.

The data collection method is an important aspect as scanner systems are developing rapidly and they can be installed on an increasing number of different platforms. This is addressed clearly in the thesis as the spatial data used in the studies were measured by means of aerial, mobile, or terrestrial small-footprint laser scanners. Furthermore, the spectral data were collected with an airborne camera in one study, and with different hyperspectral sensors attached to terrestrial or mobile platforms in the three other experiments.

1.3 The Dissertation's Objectives

The main objective of the present dissertation is to depict the study and development of methods needed for individual tree species classification. This classification objective is divided into four subobjectives and each of them is investigated in separate studies. The results obtained from the four studies are then discussed to provide an insight for recommended practices on how to plan classification experiments that use combined remote sensing data collected with airborne, mobile, or terrestrial sensor systems. In the discussion I also proceed to outline the feature selection and classification practices that were found to perform the best with the studied data. Moreover, the development of future sensor systems is discussed based on the obtained results with the aim of further improving tree species classification accuracy and data processing efficiency.

The first subobjective was to determine the possibility to use directional lighting and light detection data to improve tree species classification accuracy when applying the airborne approach. The study was performed by dividing individual tree crowns shown on airborne false-colour imagery into illuminated and shaded parts. The data thus obtained were then used in the classification stage. The division of tree crowns was determined from a digital surface model (DSM). The raster DSM was calculated from LiDAR data.

The subobjective in the second study was to concentrate on carrying out individual tree species classification in an outdoor setting. The study was among the first of its kind in world at the time of its publication. It demonstrated successfully how combination of mobile, close-to-ground, laser scanning data with passive hyperspectral data were able to classify tree species on individual tree level. The spectral dataset and a point cloud were collected simultaneously and merged. Then, the classification performance of the merged dataset was studied. Both datasets were collected with sensors attached onto a fixed platform. The platform was mounted on an automobile. The spectral data were collected using a passive line spectrometer and the point cloud was collected using a low-resolution laser scanner.

The third subobjective was to simulate the use of actively scanned hyperspectral data and their performance in individual tree species classification. The study was also one of the first utilizing this type of data fusion in individual tree species classificaiton. The data simulation was carried out by fusing hyperspectral data measured by means of a novel active hyperspectral laser scanner and a point cloud collected using a terrestrial laser scanner. The experiment was carried out in laboratory conditions, which allowed the minimization of external effects and precise radiometric calibration.

The fourth subobjective was to determine whether artificial surfaces are applicable as gray-scale references for remote sensing studies. It is possible to collect spectral data with no rigorous radiometric calibration and still get relatively accurate tree species classification results within one dataset measured over a short time interval. However, it is highly unlikely that one can reach similar classification results when tree species are classified from data consisting of two or more datasets that have been collected at different times and in different places. This is due to significantly different directional and temporal lighting conditions present in each case. Thus, rigorous radiometric calibration is essential if data from two or more separately measured sites and times are to be compared together. The radiometric calibration can be performed with transferable calibration targets that are placed in the measurement area, but this technique is time-consuming and it becomes inpractical with increasingly bigger measurement areas. The directional radiometric measurements used in the study were collected using the Finnish Geodetic Institute's Field Goniospectrometer (FIGIFIGO).

1.4 The Structure of the Thesis

The present dissertation is divided as follows: Chapter 1 presents the research hypothesis and the objectives of the dissertation. Chapter 2 presents the most important and the most recent literature and results related to the field of the dissertation. Chapter 3 presents a summary of the data and methodology used in the studies conducted. Chapter 4 summarizes the results obtained in Studies **I-IV**. Chapter 5 discusses the findings and the importance of the results presented in Studies **I-IV**. Chapter 6 consists of the summary of the dissertation and an outlook regarding future research topics of interest.

Chapter 2

Review

2.1 Remote Sensing Techniques Used in Forest Classification Studies

The successful classification of different forest types and individual trees requires that their characteristics can be mapped with sufficient accuracy. The characterizing features can be extracted from one or several different domains that include the spatial domain, the spectral domain, the radiometric domain, and the temporal domain. The effectiveness of classification of a feature set depends on the number and the separability of the selected features. Depending on the measurement setup and the sensors, usable classification features can be generally separated from one or two different domains at a time.

If the initially selected features fail to provide the required classification performance, then one can try using additional features to achieve improvements in results. However, if the classification task is complex, it may happen that the classification cannot be carried out with the desired accuracy in one or two data domains. In such cases, additional data from other domains are needed and they need to be collected using different sensor systems. The use of data from different domains significantly enhances feature separability. This simplifies the classification task. However, simultaneously collected multi-sensor data are rarely available. Moreover, data combination processes are seldom straightforward, and they require several intermediate steps before feature extraction from combined data is possible.

In forest remote sensing, tree geometry and its other spatial features are usually extracted from point clouds. The point clouds are collected using laser scanners as they provide the form of objects in three dimensions. The best way to collect spectral features is to use multi- and hyperspectral sensors. Both spatial and spectral features can be extracted simultaneously from traditional imagery, but the number of detectable features they can provide is limited in both domains.

The following paragraphs provide an overview of classification of forest types and tree species, and of the data collection techniques applied in forestry research. The presentation considers only the remote sensing techniques that were utilized in the studies included in the thesis. Therefore, mid-to-long wavelength infrared and microwave (RADAR) remote sensing are excluded from the technical review. The same applies for the methodology review in section 2.2. The technique descriptions are treated on a basic level as there is a lot of variability with sensor systems. However, the working principles of the sensors are similar. The data collection techniques used in Studies **I - IV** are described in more detail in each respective study.

2.1.1 Laser scanning

Measurement systems that send coherent laser light towards a target system and then detect the backscattered radiation to analyze target properties are called Light Detection and Ranging scanners (LiDARs). The first LiDAR systems were introduced in the 1960's, but their use had a relatively slow start due to lack of supporting instrumentation. However, a variety of laser systems is now in use in several and diverse fields of research. In the atmospheric sciences they are applied in the detection of aerosol size and composition, wind monitoring, gas detection, and chemical reactions studies [3]. In topographic studies, LiDARs are used in terrain profiling, scanning, and modeling [4]. LiDARs have also been found useful in many specific research fields such as archaeology, agriculture, urbanization, and fluvial studies [5–8].

The basic working principles of LiDAR systems are similar regardless of the application. The main parts of a LiDAR system are a transmitter for generating the laser beam, and a detector for collecting the reflected radiance. Both the transmitted beam and the reflected beam are usually enhanced by means of optics. In most cases, both beams are directed along the same optical path to simplify the detection geometry. The back-scattered radiation is collected by means of an electronic detector into the system that handles data storage and possible preprocessing steps.

In addition to the laser ranging unit, a LiDAR system needs also a scanning mechanism for collecting the data from a wide area. The scanning pattern depends on the design of the scanning mechanism and it can be performed by means of several different methods. Common scanning patterns include parallel, elliptical, sinusoidal, and zig-zag [9]. As a single dataset may contain tens of millions of points, it is of importance that the point collection is performed in an efficient manner. Figure 2.1 illustrates the basic parts of a laser scanning system. The illustrated system is an active hyperspectral laser scanner prototype developed and constructed at the Finnish Geodetic Institute (FGI) [10]. Commercial scanner systems embody similar principles, but with structure and casing being more integrated and more compact in size.

Modern LiDAR systems include also separate application-dependent instrumentations. For example, accurate positioning and attitude data are needed in topographic studies and in mapping. These are obtained by means of GPS (Global Positoning System) and IMU (Inertial Measurement Unit) sensors, which are essential for geo-referencing.

LiDARs collect data by means of two main methods: either by sending individual laser pulses or by sending a continuous laser beam that is phase-modulated to allow precise ranging (Figure 2.2). With pulsed measurement, the range of the scatterer from the scanner is calculated from the laser pulse travel time as follows:

$$R = \frac{1}{2} vt \tag{2.1}$$

where R is the object distance, v is the known speed of electromagnetic radiation, and t is the total travel time of the laser pulse.

Continuously measuring laser devices determine object distances by modulating the transmitted laser beam with a signal that has a known frequency. Here, an amplitude-modulated (AM) version is presented. When the reflected beam returns to the detector, the distance can be calculated from the phase difference between the transmitted and the detected laser beams:

$$R = \frac{1}{2}(M\lambda + \Delta\lambda) \tag{2.2}$$

where λ is the modulation signal wavelength ($\lambda = vT$ with T being the time of a modulation period), M is the integer number of full modulation signal wavelengths, and Δ is the fractional part of the modulation signal wavelength. The form of the Δ is $\frac{\varphi}{2\pi}$, where φ is the phase difference between the transmitted and the returning beams. State-of-the-art scanner systems perform the laser beam modulation with several modulation frequencies to increase their range detection accuracy.

2.1.2 Spectral imaging

Geometric properties offer an efficient way for recognizing different object classes. In addition to laser scanning data, geometric data can be also collected from imagery. This field of study is known as photogrammetry [11]. Another way to recognize objects is to extract their spectral and radiometric information contained in images. This technique is called spectral imaging. However, the differentiation of

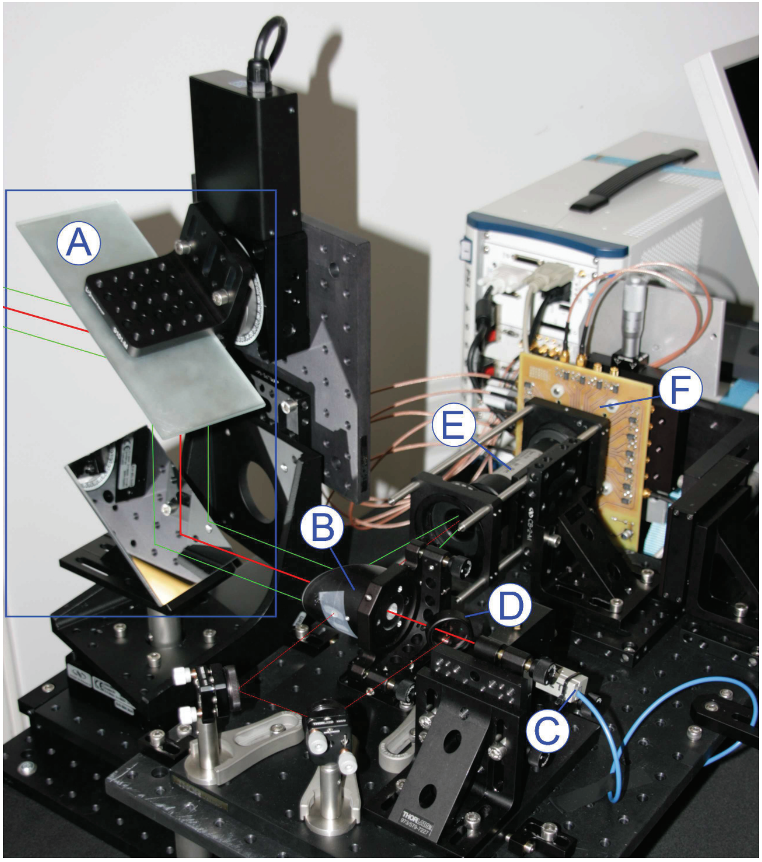

Figure 2.1: The basic structure of a (hyperspectral) LiDAR system. **A** A 2D scanner made up off two rotating mirrors; **B** A light collecting, parabolic off-axis mirror; **C** A transmitted laser beam, brought along the optical fiber from a laser source (not shown in the figure); **D** A laser beam splitter used to produce trigger pulses; **E** A spectrograph that separates different wavelengths (not needed in ordinary LiDAR); **F** Receiver electronics that record and convert incoming laser pulses into digital form. *Photo by Teemu Hakala.*

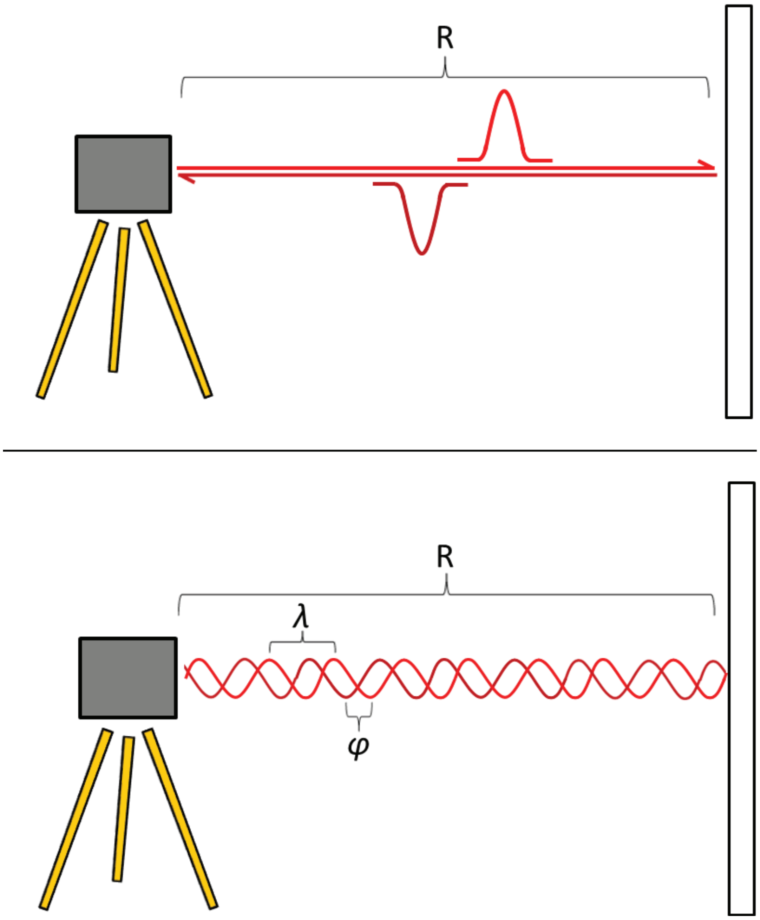

Figure 2.2: Laser scanner based range detection principles in a pulsed and in a continuously measuring system. The upper figure represents a pulsed laser system that detects the range to an object based on the travel time of a laser pulse. The lower figure represents a continuously measuring laser system that determines the range to an object from the phase difference between the transmitted and the incoming laser beams. R is the object's distance from the scanner, λ is the wavelength of the modulating signal, and φ is the phase difference between the two laser beams.

the spectral components from an analog film image is a difficult task. Thus, systematic and quantitative use of spectral and radiometric data in object recognition has become more common since digital imaging systems came available.

The naming convention of spectral imagery is related to the number of detectable wavelength channels, their widths, and sensitivities [2]. Monochromatic images contain spectral information from a single narrow wavelength region. Panchromatic imagery have also spectral data recorded in a single channel, but they cover a wide wavelength area and their spectral response may not be uniform in all parts of the spectrum. Multispectral imagery consists of several separate channels, where each channel covers a sensor-specific wavelength band. The number of bands, their widths, and sensitivities are system-specific. Also, the wavelength bands can be located close to each other or they can be in different parts of the spectrum. Some overlap is also possible between multispectral channels. Hyperspectral imagery can detect at least some tens or more separate wavelength channels. The hyperspectral channels are usually narrow and they are located next to each other in the spectrum with very little, if any, overlap. Also, the hyperspectral channels have equal widths. Figure 1.2 illustrates the differences between the various types of spectral imagery.

The large-scale use of spectral imagery began when the first multispectral data-collecting satellite, LandSAT-1, was launched in 1972. It took images covering an area of 185 kilometers by 185 kilometers with a GSD of about 80 meters by 80 meters [1]. Each image pixel had four spectral channels. To date, the Landsat program has launched a total of seven satellites, and of these two are still operating. The goal of the Landsat program is to observe and provide data on the Earth. The Landsat data have been used in several fields of research over the past four decades. Other satellites carrying multi- and hyperspectral sensors and monitoring the Earth are the French SPOT series (Systéme Probatoire d'Observation de la Terre), European Space Agency's (ESA) MEdium Resolution Imaging Spectrometer (MERIS), NASA's Moderate-resolution Imaging Spectroradiometer (MODIS), Lockheed Martin's commercial IKONOS satellite, and the Japanese Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), to name some of them [12–16].

There are also several airborne systems that carry hyperspectral sensors. NASA has built an Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) [17]. Commercial hyperspectral mapping systems, such as HyMap (Integrated Spectronics Pty Ltd., Australia) and Compact Airborne Spectrographic Imager (CASI) (Itres Instruments, Calgary, Canada), provide data for monitoring environmental pollution, agriculture and forestry, soil mapping, vegetation assessment, and water quality [18–20]. Another commercial hyperspectral system is the Finnish AISA (Spectral Imaging Ltd., Oulu, Finland) that has been utilized in bathymetry, water

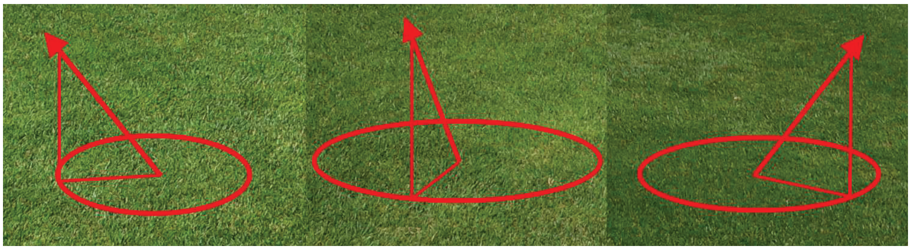

Figure 2.3: Directional lighting effects in practice. A patch of grass photographed with the same camera settings and a one minute interval from three different viewing angles. The arrows point towards the sun. These photographs were taken on a football field in July 2007. The lighting conditions did not change while the photographs were taken. *Photos by Juha Suomalainen.*

quality studies, archaeological research, and in forestry [21, 22]).

The improved instrumentation has also made portable spectroradiometers available for ground measurements. The first such commercial device was Analytical Spectral Device's (Boulder, Colorado, USA) Personal Spectrometer 2 that was introduced in 1990. Since then, portable spectroradiometers have been applied successfully in numerous field studies, e.g. in providing accurate spectral information for air- and spaceborne system reference in the field, for validating radiative transfer models, and for environmental monitoring in general [23–26].

2.1.3 Radiometric calibration

Spectral imagery

One of the main challenges in spectral imagery is the measurements' dependency on external lighting sources and changes in them. The causes of variance might be environment related, such as shading, or directionality related, especially in cases where viewing geometry is close-to horizontal. Figure 2.3 demonstrates the variance in the detected incoming radiance, when a flat target is viewed from different sides over a short period of time. Thus, the dependency on external lighting sources imposes considerable limitations on data collection and requires an extra effort in calibration. Radiometric calibration methods in spectral imagery depend on the sensor platform: spaceborne systems can be calibrated with onboard calibration references [27] or by using atmospheric correction, different radiative transfer models, and field measured references [28]. Spectral imagery collected by means of airborne systems is often calibrated using methodology similar to that used with spaceborne collected data. However, as airborne data usually have significantly better spatial resolution than the data collected by means of spaceborne systems, it is also possible to use relatively small portable reference targets with known reflectance responses [29, 30].

There is also growing interest being shown towards building permanent test sites that include carefully selected calibration targets for performing simultaneous geometric, spatial, and radiometric calibration. Honkavaara *et al.* have tested the benefits of test field calibration and their results have shown that the use of a specially-built test field is an important part of the system calibration chain [31]. However, they emphasize that a comprehensive sensor-calibration procedure should include laboratory calibration, test field calibration, and product level validation [32]. Their recommendation is that at least all quantitatively collected parameters should have test field calibration.

Reference measurements for both spaceborne and airborne radiometric calibration include reference target measurements in the field. The reference data are collected by means of portable spectrometers and spectrogoniometers [33–35]. Radiometric reference data are also collected from large natural surfaces that have relatively good spatial uniformity and are temporally stable. Such target areas include salt flats, glacial ice, and deserts [36]. At ground level, both in the field and in laboratory measurements, radiometric calibration is often performed using specially made diffuse reference targets, such as Spectralon® (Labsphere Inc, New Hampshire, USA), that are very close to Lambertian scatterers over a wide spectral range.

Another issue adding to the complexity of radiometric calibration is that it needs to be repeated frequently. The reason is that lighting condition changes are likely during measurement. Thus, novel ways to reduce the effects of lighting condition changes are being studied and presented: new active spectral imaging sensors have been developed. These sensor systems are able to produce a continuous spectrum with a laser source and non-linear optics [37,38]. The reflected spectrum can then be detected either as separate wavelengths or as a whole spectrum. Active imaging setup offers several advantages over the conventional measurement setup: as the transmitted spectrum and its intensity are stable and known, repeated calibrations are not needed during measurements. Also, the transmission and the detection geometry of an active system are similar, which simplifies the correction of directional lighting effects (see Figure 3.1). Moreover, there is hardly any shadowing in the detection scene of active spectral imaging.

Laser scanning

The first laser scanners were built for ranging purposes. Thus, it was imperative that the travel time of a laser pulse, or the phase change of a continuous laser beam, could be determined as accurately as possible. However, the intensity of backscattered laser beams varies significantly depending on the target type that the beams hit. This adds to the uncertainty of ranging as excessively intense returns may saturate the receiver and create so-called 'ghost' points. On the other hand, a very weak laser return does not trigger the receiver at all and such a return signal is missed completely. To prevent errors related to laser return intensity, most commercial LiDAR systems have built-in feedback loops that monitor laser return intensity and adjust transmitter power accordingly to regulate laser intensity within the detection limits. However, automatic intensity adjustments prevent direct usage of radiometric data in situations where intensity correction has been applied. This is because autocorrection algorithms are scanner-dependent and manufacturers do not make them available [39]. Thus, range-dependent and directional intensity corrections on laser data have to be performed by conducting separate empirical studies.

The utilization of laser scanner intensity information is important. This could provide additional knowledge for forestry, glaciology, and urban research [40–42]. In addition, intensity correction provides valuable help for temporal laser scanning studies and for local geometric matching between different scanlines [39]. Laser scanner intensity calibration has attracted increasing interest in recent years. Several studies about laser scanner intensity calibration have been published in laboratory and in field conditions using both airborne and terrestrial scanners (e.g. [39, 43–47]). Also, new calibration methods should be readily transferable to multiwavelength laser systems when the new systems become more available.

2.2 Remote Sensing Research in Forestry

2.2.1 Airborne imagery

Forests have been analysed from photographs already since the 1940's using photogrammetric methods. The aims of earlier forest research were mainly the same as at present. The studies were conducted to provide information on forest monitoring and management, forest modeling, and assessment of damage caused by insects, fires, winds, and snow. Also, single tree properties have been studied extensively. Such properties have included, among others, tree height, crown measures, and diameter at breast height (dbh) [48]. The colour information provided by aerial photographs has been also used in discriminating coniferous and deciduous trees and in tree species classification. The main disadvantage in the use of aerial photographs is that trained professionals are needed for the work and that visual interpretation is time-consuming and expensive [48]. Moreover, it is common for different tree species to have similar features, either in the spectral or spatial domain. Furthermore, there is a trade-off between the spectral and spatial performance depending on the camera used. Thus, the most beneficial approach for classification purposes has often been to combine image information with data from other sources.

Multiple channel and hyperspectral imaging have been utilized in forestry since they became available [49, 50]. The earliest studies concentrated on land cover analysis and change detection. Tree species classification has always been an important research topic making significant use of the spectral data collected over a wide spectral range [51–55]. For example, Meyer *et al.* achieved an average classification accuracy of 80% in a study where healthy and damaged spruce, pine, fir and beech trees were classified semi-automatically using CIR images. The imagery had resolution of 0.5 meters [54].

Spectral imagery are also used widely in research looking into vegetation and forest canopy reflectance, and their modelling [56–58]. Spectral information makes it also possible to map and determine both biochemical and biophysical components of forests and their canopies [59, 60]. Forest fuel research requires accurate spectral data to distinguish and assess the amounts of different fuel components present in studied areas [61]. Furthermore, spectral imagery have been utilized to in the study of large-scale forest succession [62], regrowth rate changes [63], and phenology changes in a forest after selective cuttings [64].

2.2.2 Airborne laser scanning

The first reported forestry studies applying laser data date back to the late 1970's and early 1980's. At first, the laser data were collected by means of aircraft-mounted profilometers to create height profiles of forest stands, but the studies were soon extended to estimation of tree heights, stem volumes, and biomass (e.g. [65–69]). However, it took until the late 1990's before the integration of airborne instrumentation (ranging frequency, scanning techniques, and GPS and IMU sensors with the required recording capabilities) had developed to a level where small-footprint laser scanning studies became possible. 'Small-footprint' refers to laser spots that are between $0.2 - 2.0$ meters in diameter [70]. Moreover, the collection of high-quality laser scanning data requires that the intrinsic properties of the measurement system are known thoroughly. Properties such as laser beam divergence, receiver sensitivity, laser scanner power, and total backscattering energy all affect the quality of a point cloud [65, 71, 72]. Also, flight altitudes and scanning angles have to be taken into account when planning measurement processes [73, 74]. Furthermore, the type and density of scanned vegetation also affect the ratio of recorded first and last laser returns [75]. A laser beam interacts in several different ways when it passes within or through a tree canopy. This results in multiple returning signals or a continuous waveform for each transmitted signal. This additional information can be utilized to improve forest parameter extraction at both tree and stand level. The point cloud densification by utilizing multiple return and full-waveform data has gathered increasing interest in forestry research. In recent years, Wagner *et al.* have carried out several studies to determine the most crucial factors needed in multiple return and full-waveform laser echo detection [76–78].

At present, state-of-the-art airborne systems have point repetition frequencies of over hundred thousand points per second at low altitudes [79]. The data are typically processed by creating first a digital terrain model (DTM) for estimating ground surfaces, and a digital surface model (DSM) for estimating the shapes of above-ground objects. The surface model can be normalized by taking the difference between DSM and DSM to form a normalized DSM (nDSM). The nDSM is also referred as the canopy height model (CHM) when all above-ground data come from the vegetation. The models can be calculated using either an original point cloud or by making a height raster map [79]. With a ground model, it is possible to derive the desired characteristics and features only from above-ground points and use them in area-based or individual tree analysis.

Small-footprint laser data have been applied in a wide variety of forestry applications including terrain detection in forests [80, 81], stand-wise and individual tree height detection [82], tree number and volume estimations [83–85], and forest change detection [86, 87]. Additionally, voxelized LiDAR data have been exploited in the estimation of crown base heights of both deciduous and coniferous trees [88].

The overall performance of ALS data has made the data a viable option for commercial and operative forest inventories when dealing with only a few dominant and commercially significant tree species. Hyyppä & Hyyppä showed that laser scanner accuracy was higher in stand attribute retrieval than was the case with the other tested optical remote sensing data sources [89]. In addition, both Naesset *et al.* and Maltamo *et al.* have found ALS data sufficient for operative use in forestry; their summaries focused on studies performed in Nordic countries during the 1990's and 2000's [72, 90].

ALS has been also applied extensively in tree-species classification [40, 91–95]. LiDAR intensity data have been exploited for this purpose because they are free of shadowing [92, 94]. Donoghue *et al.* [92] used range-corrected intensity measures to compute different height quantiles in forest stands. The quantiles were used to quantify the volume of spruce in even-aged, mixed stands of spruce and pine. Ørka et al. [94] used structural features together with range-corrected, first-return pulse intensity data. They achieved an overall classification accuracy of 88% for spruce and birch. Kim *et al.* [93] used temporal LiDAR intensity data to classify tree species in both leaf-off and leaf-on conditions within the same forest site. The test site was located in the Washington Park Arboretum, Seattle, Washington, USA. Eight deciduous and seven coniferous tree species were included in the study. The resulting classification accuracies between deciduous and coniferous trees were 73.1% for the leaf-on dataset, 83.4% for the leaf-off dataset, and 90.6%, when all datasets were used.

2.2.3 Terrestrial laser scanners

Large-scale forest and ecology studies are usually performed with airborne laser scanners. The validation of the large-scale results is done by conducting ground measurements. The researchers collect data on the parameters describing the health and characteristics of trees from selected test plots [96–98]. The collection of the validation data is mainly manual work and its speed and accuracy depend largely on the experience and skills of the people doing the work.

Terrestrial laser scanning (TLS) has, over the past decade, been shown to be a practical technique for forest parameter retrieval. TLS provides high accuracy spatial data that scales from a single tree to plot level. Moreover, TLS data collection is more effective in terms of cost and labour than when using conventional methods. Thus, TLS provides an effective way to measure and analyze important forest parameters. TLS data have found use in several applications over recent years. These applications include parameter collection for tree and stem locating, measurement of tree height and diameter, canopy structure modeling, and estimation of the canopy gap fraction [99–108].

TLS data collection can be performed by means of a single scan or multiple scans. These data are usually collected at plot level. Single-scan data collection is fast both to collect and to process [100, 102–104]. Furthermore, the single-scan data processing can be readily automated. However, single-scan measurement setups are highly sensitive to any occlusions present in the measurement area. This is a clear downside as there is always some degree of occlusions in forest conditions, even in sparse forests. Multiple-scan measurements provide a higher level of detail than do single-scan measurements. They also provide a better coverage of the scanned area. Additionally, multiple-scan measurements are less sensitive to occlusions. The downside of multiple-scan data collection is that the collection times are significantly longer. Also, automatic data processing and analyses are not feasible before the data from all scans have been co-registered and combined [100].

2.2.4 Forestry studies with combined methodology

The simultaneous use of laser scanning data in combination with multi- or hyperspectral imagery has been a topic of large interest for several years. Especially, combined airborne data have been collected for the purpose of forest assessment and ecological studies [109–122].

New methods have been developed in the Nordic countries to utilize combined airborne data in the classification of single tree species [116, 123]. These methods include the use of range-corrected ALS intensity, and data fusion with aerial imagery. The methods have proved to be successful in the classification of dominant tree species.

Korpela *et al.* integrated LiDAR data with aerial images and used them to classify seedling trees in a raster cell setup with an approximate resolution of 0.5 m [116]. Conifers, deciduous broad-leaved trees, other low vegetation, and abiotic surfaces were used as reference classes. The achieved classification accuracy varied among the study stands with a minimum of 61.1% and a maximum of 77.8%. The corresponding minimum and maximum accuracies changed to 61.6% and 78.9%, when the used sample trees were limited to those in direct sunlight. They also noted that the LiDAR intensity data were not sufficient to separate the three main species of forest trees in Finland.

Persson *et al.* carried out a study where they integrated aerial color-infrared (CIR) imagery and LiDAR data to classify trees into three classes: spruce, pine, and deciduous [123]. The tree segmentation was done using LiDAR data. Then, the tree segments were mapped onto the corresponding aerial image. The tree species classification was done using 10% of the brightest pixels of each tree crown. Each chosen pixel was represented by two angle values, which were calculated from the green, red, and infrared components of the pixel. A sample tree was represented by the mean of the pixel angle values within the tree segment. Spectral-band ratio filtering was suggested as a means of reducing the shadowing effects. They reported an overall classification accuracy of 90% for the training set. A spectral rationing algorithm and the formation of a hybrid color composite image has been also used in other studies to reduce shadow effects, e.g. Bork and Su [111].

The number of dominant tree species is small in the Nordic countries. Also, there is not as much variation in the canopy structure as there is in more temperate regions. The task of classifying dominant tree species and vegetation types becomes increasingly difficult when both the species number and tree density increase. However, an approach that first separates tree canopies from the LiDAR data and then classifies them based on spectral information has been shown to work in more temperate regions. Waser *et al.* used this approach to classify five tree species from aerial images taken with ADS40 and RS30 digital cameras [122]. Their training set consisted of color-infrared (CIR) images. Their approach resulted in an overall classification accuracy of 86%.

Heinzel *et al.* also delineated trees from a LiDAR-derived digital surface model (DSM) [124]. Then, they made a color-space transformation to the histogram-linearized CIR true orthophotos. The original CIR color channels were transformed into hue (H), saturation (S), and intensity (I) channels. Then, a polygon of a delineated tree was fitted to the spectral data. Shaded areas with very low intensity values were removed. The classification was carried out in two steps: firstly using the hue channel histogram and secondly using the NIR band. The overall classification accuracy for the tree classes of mixed oaks and hornbeams, beeches, and coniferous trees was 84%.

Dalponte *et al.* tested combined hyperspectral imagery and multiple-return ALS data to classify 23 land classes [112]. They obtained class-wise accuracies of over 85% for the dominant classes.

There is an increasing need to automatically obtain tree data on trees and forests in urban areas. ALS methods have been already developed for this purpose [125, 126]. An alternative way to collect tree data in urban environments is to use Mobile Laser Scanner (MLS) systems, whose number has started significantly to increase during the past few years. MLS systems usually include one or more cameras and/or spectrometers in addition to one or more laser scanners. This allows simultaneous collection of both high-density spatial and spectral data. Combined MLS data are already being used in creating photorealistic models of urban and suburban areas of cities [127, 128]. Moreover, the first MLS studies focusing on forestry studies in urban environments have been published [129, 130]. However, the spectral data collected using MLS systems have not yet been fully utilized in analytic classification of tree species. One limiting factor is that of horizontal viewing angles, which change often and rapidly when an MLS system moves in an urban environment. This presents a significant challenge for proper radiometry calibration as the platform's lighting status changes constantly.

All in all, several different approaches exist in the endeavor to extract important forestry parameters with a high level of accuracy. However, these approaches are usually associated with specifically collected datasets. Therefore, methods characterized by high performance do not succeed with the same high level of accuracy when they are applied to other data. This has been clearly presented in a EuroSDR tree extraction project, where different extraction methods were tested on freely available datasets [131]. The project took place in 2008 and twelve different research groups participated in it. Tree species were classified by only two participants. Their tree species classification results were 78% correct when using airborne photographs (57% of the trees were classified) and 54% correct when using laser data (64% of the trees were classified). These results are of interest because the classification percentages demostrated significant variation between the obtained results and earlier results. Articles presenting classification methods had shown classification accuracies of over 80%. Kaartinen *et al.* assumed that the earlier results indicating high performance had been obtained through having controlled conditions. The EuroSDR study showed that the tree classification accuracies published in the joint test did not match the results obtained earlier. The conclusions of the EuroSDR study were that a) there is a need to develop new methods that would work in non-optimal forest conditions and that b) more method comparison studies should be carried out.

Chapter 3

Materials and Methods

The chapter is divided in three sections. The first section gives an overview of the data collected and analysed in studies **I - IV**. The second section outlines the concept of reflectance and its physical background, which were needed in the analysis of study **IV**. The final section gives an overview of the working principles of the two classification methods used in tree species classification in Studies **I - III**. The final section also describes shortly the type of classification features utilized in the studies.

3.1 Data Used in Different Studies

The data collected in Studies **I**, **II**, and **III** resemble each other in that they were collected for the purpose of tree species classification. The data contain both spatial laser point data and multi- or hyperspectral intensity data. Laser scanning data and intensity data were combined in all three studies to form merged datasets for the purpose of classification. Apart from these, the measurement techniques used in collecting the data were different.

In Study **I**, airborne data were collected using an Optech 3100 ATLM airborne laser scanner system (Optech Inc, Vaughan, Canada) and InterGraph's Digital Mapping Camera (Intergraph Corporation, Huntsville, USA). The dataset consisted of 295 tree specimens that represented three tree species. The tree specimens were manually delineated from data.

In Study **II**, the measurements were perfomed using an FGI-built mobile mapping system, Sensei [132]. The Sensei system carries an Ibeo Lux laser scanner (Ibeo Automotive Systems Gmbh, Germany) and a Specim V10H line spectrometer (Spectral Imaging Ltd, Finland). The combined dataset consisted of the total of 168 individual tree specimens representing over 20 different species.

In Study **III**, laser scanning data were collected using an FARO Photon^{TM} 80

Table 3.1: The laser scanners used in the Studies **I-III** to produce and collect laser point clouds of the studied objects.

Study	Sensor	Type	Point density (n/m^2)	Date
I	ALTM 3100	ALS	9 - 12	July 2005
II	FARO Photon^{TM} 80	TLS	10^3	Aug 2009
III	Ibeo Lux	MLS	10^2-10^3	Sep 2010

terrestrial laser scanner (FARO, Lake Mary, USA). Hyperspectral laser scanning data were collected with a FGI-built measurement system [133]. The system used a Koheras SuperK laser source (NKT Photonics, Birkerød, Denmark) to produce a hyperspectral laser beam which was detected using an Avantes AvaTech-3648 spectrometer (Avantes Inc, Broomfield, USA). The combined dataset consisted of 24 tree specimens of three tree species.

The data used in Study **IV** contained only hyperspectral information and they were measured using a Fieldspec Pro spectrometer (Analytical System Devices, Boulder, USA). The dataset consisted of nine asphalt targets and two control targets, beach sand and a concrete slab.

The details of the laser data used in Studies **I**−**III** are given in Table 3.1, and the details of the reflectance and intensity data used in all of the studies are given in Table 3.2.

Data processing was carried out in all four studies with different versions of the Matlab computational program (Mathworks, Natick, USA).

3.2 Reflectance

The anisotropic reflection properties of diffusely reflecting surfaces can be given using the *Bidirectional Reflectance Distribution Function* (BRDF), which is defined as the ratio of the reflected radiance $L(\theta_0, \varphi_0, \theta, \varphi)$ to the incident unidirectional irradiance $E_0(\theta_0, \varphi_0)$ as [134–136]

$$f(\theta, \theta_0, \varphi, \varphi_0) = \frac{dL(\theta_0, \varphi_0, \theta, \varphi)}{dE_0(\theta_0, \varphi_0)}, \tag{3.1}$$

where the angles are defined in Figure 3.1. The BRDF is normally a function of four angular parameters, but the azimuth dependency can be reduced to only one angle (φ) if the target is assumed to be symmetrical with respect to the principal plane. In that case, it is enough to measure only the difference between the azimuths. This assumption holds well for flat and almost isotropic surfaces, such as asphalts. A related quantity, the bidirectional reflection factor (BRF) can be

Table 3.2: The spectrometers used in all of the studies to collect the spectral infromation. The spectral resolution is reported as FWHM in nanometers. * The wavelength range marks the range used in the studies, not the full range of the spectrometers. ** The DMC is an airborne camera system and, contrary to the other spectrometers, its channel-wise spectral resolution cannot be reported.

Study	Sensor	Light source	Wavelength range* (nm)	Spectral resolution	Date
I	DMC	Sun	400 - 850	**	Sep 2005
II	AvaSpec-3648	Koheras SuperK	500 - 900	5	Aug 2009
III	Specim V10H	Sun	397 - 1086	8.5	Sep 2010
IV	Fieldspec Pro	Sun	400 - 2300	5 (< 985 nm) 10 (> 985 nm)	May, Jul 2005 Jun-Jul 2006 May, Aug 2007

defined as the ratio of the reflected light to that reflected from an ideal Lambertian surface, for a unidirectional illumination source. BRF differs from BRDF by a factor of $1/\pi$.

For most practical purposes, sunlight can be considered unidirectional, but there is also scattered radiation coming from clouds, the environment and the blue sky. Thus, one cannot normally measure BRF directly in sunlight, but must extract it instead from the Hemispherical-Directional Reflectance Factor (HDRF). HDRF can be expressed conveniently as a superposition of a direct light source (Sun) and a diffuse component (sky irradiance). This assumption allows us to express HDRF as

$$R^{\mathrm{HDRF}}(\theta,\varphi) = \frac{L(\theta,\varphi)}{L_{ref}}, \tag{3.2}$$

where L and L_{ref} are the radiances of light that has been scattered from the target surface and from the Lambertian reference surface. The reflected radiance can be given by

$$\begin{aligned} L(\theta,\varphi) &= \int_0^{2\pi}\int_0^{\pi/2} R(\theta,\theta_0,\varphi,\varphi_0)\{L_{diff}(\theta_0,\varphi_0) \\ &+ L_0(\theta_0,\varphi_0)\}\cos\theta_0\, d\theta_0 d\varphi_0 \\ &= L_{diff} + R^{\mathrm{BRDF}}\, E_0 \\ &= R^{\mathrm{HDRF}}(\theta,\varphi)\, L_{ref}, \end{aligned} \tag{3.3}$$

where L_{diff} and L_0 are diffuse and direct parts of incident radiance.

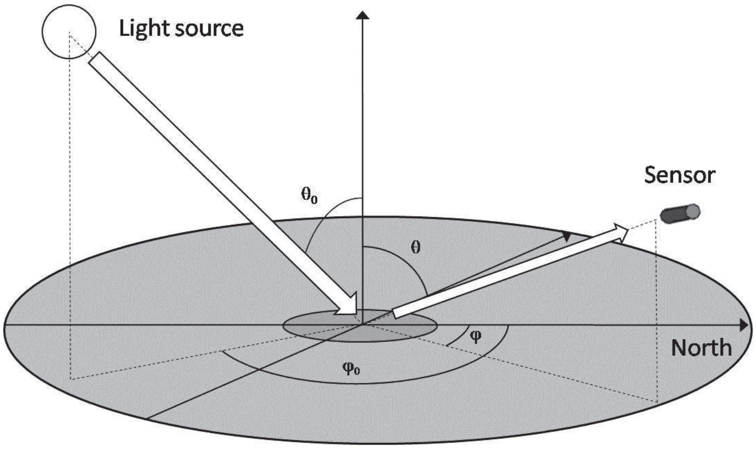

Figure 3.1: Measurement geometry of BRF where φ and φ_0 are the azimuth angles of incoming and reflected light, and θ and θ_0 are the respective zenith angles.

HDRF is both dependent on the scattering properties of the surface and the distribution of the illumination. HDRF can be reverted back into BRF if the diffuse light source contribution can be eliminated using a suitable atmospheric correction [137, 138].

The following equation can be used to retrieve the HDRFs of measured targets for a single measurement point:

$$R^{\mathrm{HDRF}} = \frac{L_T - L_{T,diff}}{L_{ref} - L_{ref,diff}} R_{ref}, \tag{3.4}$$

where L_T is the radiance reflected from measured target. The term $L_{T,diff}$ corresponds to the radiance measured from a shadowed target. It is used to eliminate the diffuse background. Terms with subindices $_{ref}$ or $_{ref,diff}$ are radiances measured for the white reference panel used. R_{ref} is the table reflectance factor of the reference panel in a similar measurement geometry. All terms, excluding L_T, are interpolated to a given measurement time.

3.3 Classification Methods Used in Data Analysis

The performance of the data selection and featuring methods presented in Studies **I**, **II**, and **III** were tested by classifying a varying number of individual tree specimens. Two different types of classification were used: Linear Discrimant Analysis (LDA) and Support Vector Machine (SVM). These two types of classifiers were selected as their theory and performance are well-known and they both have a large set of tools readily available for tackling different classification problems on several platforms. This facilitates the comparison of different feature extraction methods. Figure 3.2 illustrates qualitatively the working principles of the two classifiers.

The classifcation features applied in tree species analysis represented either structural or spectral properties of trees. The structural features were calculated from point cloud height statistics. Common structural features included height quantiles from the tree base and point fractions within a specific height interval. The spectral features were normalized spectral mean values taken over a whole tree (Studies **I-III**) or ratios calculated from or between different spectral values measured over tree canopies (Study **I**). Detailed classification feature descriptions are given in each study.

3.3.1 Linear Discriminant Analysis

Linear Discriminant Analysis aims at reducing the dimensionality of the studied feature space while retaining the class discriminating information [139]. Class discrimination is achieved by finding a feature-space matrix **W** that causes maximum separation of the classes in the feature space. The optimal class-separating feature-space vector is defined by maximizing the criterion function

$$J(\mathbf{w}) = \frac{\mathbf{W}^T S_b \mathbf{W}}{\mathbf{W}^T S_w \mathbf{W}}, \tag{3.5}$$

where S_b is a *between-class* scatter matrix and S_w is a so-called *within-class* scatter matrix. The *between-class* scatter matrix, S_b, describes the variance of class means as

$$S_b = \sum_{j=1}^{c} (\mu_j - \mu)(\mu_j - \mu)^T, \tag{3.6}$$

where μ is the mean of all classes, μ_j is the mean of the class j, and c is the number of classes. Term T describes the vector transpose. The another scatter matrix, S_w describes the squared sum of the differences of class-wise means in the transformed feature space and it is defined as

$$S_w = \sum_{j=1}^{c} \sum_{i=1}^{N_j} (\mathbf{x}_j^i - \mu_j)(\mathbf{x}_j^i - \mu_j)^T, \tag{3.7}$$

where $\mathbf{x}_j^i$ is the ith sample of class j and and N_j is the number of samples in class j. Other variables are the same as in (3.6).

It can be shown that the maximum classwise separation is achieved when the solution to (3.5) is $\mathbf{W} = S_w^{-1} S_B$. In the solution, each column of W_i corresponds to an eigenvector of $S_w^{-1} S_B$.

3.3.2 Support Vector Machines

Support Vector Machines are distribution-free classifiers, which were originally developed for dealing with binary classification problems [140, 141]. The binary limitation has since been circumvented, thus allowing multiclass problem handling. SVMs endeavor to separate two different classes from each other by fitting a hyperplane between them in a feature space that has a higher dimension than the original data. The class membership of a sample can be calculated from the sign of a discrimination function, whose form in a nonlinear case is

$$f(\mathbf{x}) = \sum_{i \in S} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b, \tag{3.8}$$

where $f(\mathbf{x})$ is the discrimination function depicting the hyperplane, α_i are non-zero Lagrange multipliers used in cost function minimization, y_i are target values, $\mathbf{x}_i$ is the d-dimensional feature space, b is the bias, and the $K(\mathbf{x}_i, \mathbf{x})$ is a chosen high dimensional kernel.

The optimal hyperplane is found by minimizing a cost function that maximizes the margin between the different classes with minimal fitting error. These criteria can be written as

$$\begin{cases} \text{maximize:} & \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \\ \text{subject to:} & \sum_{i=1}^{N} \alpha_i y_i = 0 \text{ and } 0 < \alpha_i < C, \text{ i=1,2,...,N,} \end{cases} \tag{3.9}$$

where C is the regulation parameter assigned for error control.

The classification procedure was chosen to follow the one suggested in the LIBSVM documentation [142]: All features were first scaled between -1 and 1 to avoid possible numerical problems and to set features on equal level with others. The kernel was a Radial Basis Function (RBF):

$$K_{RBF}(\mathbf{x}_i, \mathbf{x}) = Ce^{-\gamma \|\mathbf{x}_i - \mathbf{x}\|^2}, \gamma > 0, \tag{3.10}$$

where C is the previously mentioned regulation parameter and the γ describes the width of the kernel. The kernel parameters were optimized for the dataset before doing the actual classification. The parameter optimization was performed by doing several cross-validations for the data while changing the parameter values by several orders of magnitude.

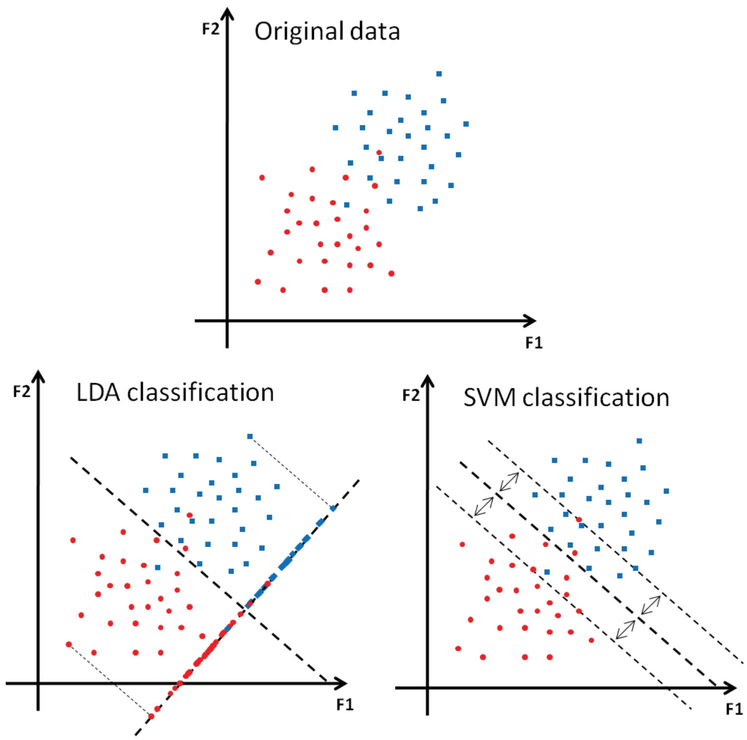

Figure 3.2: A qualitative figure representing the basic principle of the two classification techniques implemented in the present dissertation. *Top* A synthetic dataset consisting of objects that belong to two separate classes and are presented in a two-dimensional feature space. *Lower left* An LDA classifier endeavors to find a feature-space vector that maximizes the sample discrimination within the dataset when the samples are projected on the vector. *Lower right* An SVM classifier endeavors to fit an optimal separating hyperplane between the two classes. This is achieved by minimizing the cost function, whose size depends on the margin width (dashed lines) and the total error.

Chapter 4

Results

4.1 Study I: The use of pixel-wise illumination status in tree species classification from aerial imagery and laser scanning data.

The goal in Study **I** was to classify individual tree species representing three common Nordic tree genera, namely, Scots pine (*Pinus sylvestris*), Silver birch (*Betula pendula*), and Norway spruce (*Picea abies*). The tree species classification was done based on aerial imagery. The lighting status of individual tree pixels was first determined from a LiDAR-derived DSM. A new set of spectral features were derived from the pixel-wise lighting status to improve individual tree species classification. The LiDAR data and imagery were collected during two separate flights in the summer of 2005.

The reasoning behind using the pixel-wise lighting status was based on the idea that usually a significant amount of spectral data needs to be filtered out. Filtering is needed because of unstable illumination conditions and because there is always internal and external shading in canopies when the data are collected using passive sensors. Also, light penetration in the canopy structures of different tree species is known to have species-specific characteristics [143]. Thus, the use of the pixel-wise lighting status was assumed to provide additional means of distinguishing the tree species from one another.

The tree species classification was carried out by first delineating individual trees from a rasterized DSM. The delineation was performed manually. Then, both the visibility and the illumination statuses of each selected DSM raster cell were inspected. The visibility inspection was carried out by drawing a line from a raster cell towards the airplane location to check the visibility of the cell to the camera. If the line of visibility to the height raster cell was blocked, then the height raster cell closest to the camera along the line was selected instead and a corresponding height value was used for it. The illumination statuses of the selected raster cells were determined similarly after a visibility check. This time the line of visibility was drawn towards the sun and if another height raster cell was blocking the line then the inspected raster cell was labeled to be in the shade. Next, the color values of the selected raster cells were determined from aerial imagery using collinearity equations. Finally, the classification feature sets were formed by averaging over the different color channels while taking the illumination status into consideration. Figure 4.1 illustrates the height raster visibility and the shading status tests.

The species of 295 individual trees representing three genera and three species were classified using discriminant analysis. Both linear and quadratic cases were tested for the best results. The classifications were carried out using three different classification feature sets. The first classification feature set was formed from the unfiltered color pixels of each tree. The second classification feature set had been introduced by Persson et al. [123]. It was formed of heavily filtered color pixels by calculating color space feature vectors. The third classification feature set was formed using the described shading status determination. Illuminated and shaded pixels of the tree canopies were separated before using their color channel values and color channel intensity ratios in the classification.

The results showed that the new classification feature set recognized both pines and spruces with the best accuracy. The accuracies were 78.8% for pine and 55.6% for spruce. The proposed classification feature set also had the highest overall classification accuracy of 70.8%. The reference classification feature set recognized birches with the best classification accuracy of 81.5%, but it did not perform with same accuracy for the conifers, pine and spruce (45.5% and 48.9%, respectively). The low conifer recognition rate dropped the overall classification accuracy of the reference parameter set down to 64.4% for the used data. Species-wise tree recognition with unfiltered aerial image data yielded results similar to the proposed new classification feature set, but it performed with all-round lower accuracy.

The species-wise discrimination performance varied between the different classification feature sets. This knowledge was used to further improve the overall classification accuracy within the entire dataset. The combined tree species classification was performed by first classifying all birches with the refence classification features. Conifers were classified with the new classification features. Individual tree species was determined based on the posterior probabilities of the two classifications. The combined classification scheme provided a clear improvement in the overall classification accuracy and it rose to 74.5%.

The study showed one possibility to use spatial information derived from LiDAR data in enhancing classification results based on otherwise pure multispec-

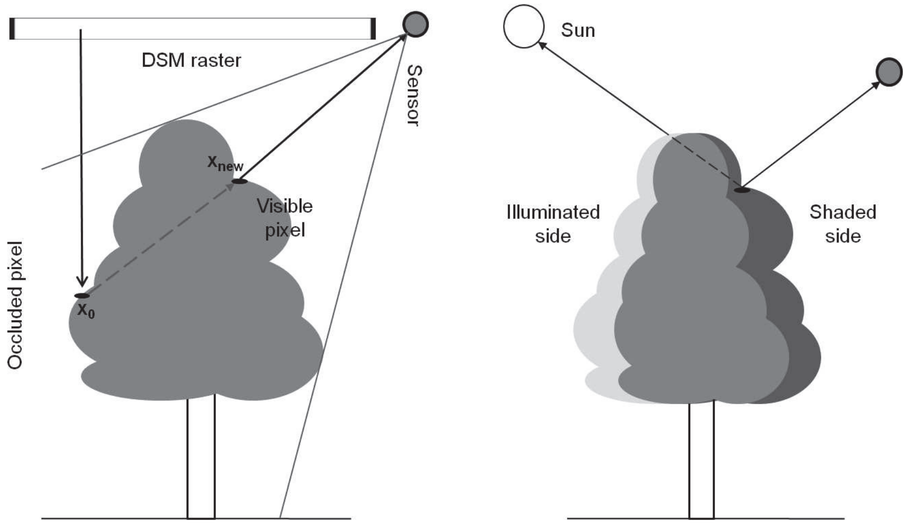

Figure 4.1: Visibility and illumination status inspections of a color pixel. *Left*) The visibility of a height raster cell (x_0) is tested by drawing a line from the cell to the scanner. If the line of visibility is blocked by higher raster cells, then the cell location was moved along the line to the closest visible cell (x_{new}). *Right*) Illumination status inspection. A line of visibility is drawn towards the sun to determine the lighting status of a visible cell. If the line is blocked, the cell is considered to be shaded.

tral data. The study also raised a new question: How to make further use of LiDAR point data instead of using them only for creating a rasterized height model of the study area? If the point cloud information could be used directly, then one intermediate processing step could be omitted. Furthermore, this would remove one source of processing-related errors from the whole process.

4.2 Study II: Tree classification with fused mobile laser scanning and hyperspectral data

The main objective of Study **II** was to test the tree species classification accuracy of a low-cost mobile mapping system. Simultaneously measured hyperspectral line spectrometer data and laser scanning data were co-registered and merged. Then, the performance of the co-registered data was tested in tree species classification. Study **II** was among the first of its kind reported in the field of vehicle-based mobile laser scanning. The number of classification features was limited. Also, the classification performance of two different kinds of classifiers, a linear

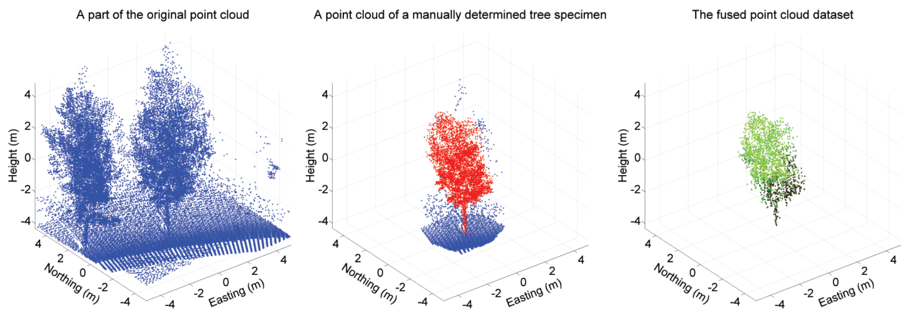

Figure 4.2: The data fusion process for a single tree specimen in an MLS study. *Left*) A single tree specimen in the original laser point cloud. *Middle*) The manually determined point cloud of the specimen. *Right*) The specimen after the data fusion process. The spectral channel values have been mapped at each individual laser point so that they each contain an individual spectrum with 123 channel values.

discriminant analyser (LDA) and a support vector machine (SVM), were tested to determine the effects of data and classifier selection on the classification results. Furthermore, different classification feature selection methods were tested to find out their effect on the results.

The study took place in an experimental garden which contains more than 200 tree and shrub specimens comprising over 20 different species. The data were collected in September 2010 using the Finnish Geodetic Institute's Sensei system [132]. The Sensei system carries a laser scanner and a line spectrometer that are programmed to take measurements simultaneously for data integration. The dataset consisted of five million laser points and close to 10,000 line spectra that covered a wavelength range of 397 nm to 1085 nm. A dataset of 168 individual tree and shrub specimens were manually determined from the data. The number of laser points for a single specimen varied from several hundreds to over ten thousand. The laser point data of the determined trees were matched with the hyperspectral data to form a fused dataset. This data matching was based on the IMU information saved during the measurement. An illustration of the data fusion process is given in Figure 4.2.

All of the determined tree and shrub specimens were used to separate coniferous and deciduous trees. Also, a subset of 133 trees and shrubs representing 10 different species were formed for species classification. The tree species classification subset was selected so that there were at least five specimens of each of the selected species. The specimens were classified with different classification feature setups: firstly, with single and paired spatial parameters derived from the determined laser point clouds; secondly, with spectral features averaged over the color data of each determined specimen; and thirdly, with the both types of data combined into feature quadruples.

A total of 34 structural features were calculated from the point clouds of each specimen. Also, the spectra measured from each specimen were divided into 123 averaged reflectance values that were used as hyperspectral classification features in the classification. The maximum number of the classification features in one classification was limited to four in the study. This limitation was imposed in order to reduce the processing complexity that increases with increasing number of classification features and their possible combinations. The classifications were carried out as leave-one-out cross validations in which each tested sample specimen was classified based on the teaching results acquired from the rest of the data.

The best classification results were obtained with the tested feature quadruples consisting of two spatial and two spectral features. The classification accuracies were 83.5% for tree species classification and 95.8% for coniferous and deciduous tree separation. The corresponding results for paired structural features were 65.4% and 90.5%, and for hyperspectral value pairs 62.4% and 90.5%. The wavelengths in the paired case were located on both sides of the vegetation infrared brightening located around 700 nm being located at 489 nm and 781 nm. The best single wavelength was located clearly in the infrared part of the spectrum, at 954 nm. Wavelengths from the same spectral area (930 nm - 1000 nm) performed also the best in discriminating coniferous and deciduous trees. The best-performing spatial features described the lower parts of the scanned trees. They represented the relative point number of over 40% of the normalized tree height, the relative point number of below 33% of the normalized tree height, and of the 20% height quantile.

The best overall classification results were obtained with the SVM classifier. An LDA classifier was also tested as a comparison. The tests between the SVM and the LDA classifier showed that the SVM performed systematically better than the LDA classifier. However, the difference between the two classifiers was limited to a few percentage points when both structural and spectral features were used together. The difference in overall classification accuracy between the classifiers grew significantly when only structural or spectral features were used. Thus, the comparison result implied that the use of the combined feature set would provide better prediction power over features derived using a single sensor regardless of the type of classifier used.

Furthermore, the effect of classification feature selection method was tested. The results were obtained by testing systematically all single features and all paired feature combinations. Then approximately 10% of the best-performing feature pairs were selected to form feature quadruples. Systematic feature testing finds the best available feature combination, but this is computationally demanding and the number of tested combinations grows in a factorial fashion. Thus, the computationally less intensive feature screening was tested in addition to find out if results of comparable accuracy could be obtained. The screening method was feature forward-selection and it was used to create feature quadruples with varying selection orders. The best overall classification result obtained with forward-selected feature quadruples was 79.7% which was a few percentage points less than the best overall classification result. Therefore, the result implied that it could be computationally more cost-efficient to screen the classification features with a (modified) forward-selection step in future studies.

The conclusion drawn from this study was that combined spatial and spectral data had significantly higher classification accuracies than single-sensor data. In addition, it was shown that the combined data could be collected with a low-cost scanner system and that the total number of classification features could be limited to only a few. However, further improvement of results and their explanatory power require additional study where the focus should be on data collection and processing, and on calibration of directional illumination effects.

4.3 Study III: Tree species classification from fused active hyperspectral reflectance and LiDAR measurements

Study **III** tested the possibility of using combined single-wavelength and actively-scanned hyperspectral data in combination in tree species classification. The study had two objectives: firstly, to show that a combination of laser scanning data and actively-measured hyperspectral data can produce an accurate overall tree species classification; and secondly, to show that good results could be achievable with a small number of classification features. The hyperspectral data were collected using a prototype system constructed at the Finnish Geodetic Institute. The system is capable of sending a hyperspectral laser pulses within the wavelength range of 500 nm and 2400 nm [133]. The wavelength range used in the experiment was limited to 500 nm and 900 nm because of the detector efficiency. A commercial LiDAR scanner, FARO Photon^{TM}, was used to measure the point cloud data as the hyperspectral laser system had no ranging capability. The data were collected from the same spot with both scanners and combined to form a fused hyperspectral point cloud dataset. Hyperspectral point clouds of the total of 24 tree specimens were measured for the purpose of classification. The test trees were young individuals of three common Nordic tree genera and species, namely Silver birch (*Betula pendula*), Scots pine (*Pinus sylvestris*), and Norway spruce (*Picea abies*). Figure 4.3 illustrates individuals of each species.

The tree species classification was performed using a support vector machine (SVM) as a classifier. The classificaions were carried out as leave-one-out classifications in which each test specimen is classified based on the teaching result obtained from the rest of the data. The point cloud shape of each tree specimen was used to derive 40 different shape-based classification features. The hyperspectral classification features were calculated as averages of 401 wavelength channels that had first been filtered to remove the contributions of dark background and the bright reference target. The tree species classification was performed three times: first with the single and paired shape-based features, then with the single and paired reflectance values, and finally with feature quadruples consisting of two shape features and two reflectance values. All single features and feature pairs were tested systematically during the classification. The feature sets with feature quadruples were formed by pairing shape-derived and hyperspectral feature pairs with over 85% classification accuracies. A screening was performed to reduce the total number of the feature quadruples tests.

The results of the experiment were as follows: the best species-wise classification results with shape-based features were 83.3% for a single feature and 95.8% for the best feature pairs. The corresponding results for the reflectance values and their pairs were over 80% for the best single reflectance value and over 90% for the best reflectance value pairs. The best combined feature quadruples were capable of classifying all tree specimens. Also, 67.3% of all tested 32,760 feature quadruples classified the tree specimens with an accuracy of over 90%. In general, the best-performing shape-based features were found to describe the top and the middle sections of a tree specimen. The best reflectance values were usually located in the wavelength bands between 530 nm and 620 nm, and between 660 nm and 720 nm.

Study **III** showed that active hyperspectral laser data combined with TLS data can be utilized in enabling accurate object classification. Moreover, then the classification could be carried out with only a few classification features. This means that the measurement equipment can be developed to detect only specific spatial characteristics and wavelengths to make data collection and processing efficient. The data were collected in the study with two different sensors. Thus, the next step in development would be to develop an integrated system that is capable of collecting multispectral range data [10].

4.4 Study IV: The possibility to use asphalt surfaces as calibration targets in reflectance measurements

The objective in Study **IV** was to examine if asphalt surfaces of different ages and wear levels could be considered as gray scale calibration targets in aerial imaging.

The possibility to use asphalt surfaces as gray scale calibration targets supports the radiometric calibration process by making it more straightforward. There would be no need to bring external calibration targets into the target area.

For an asphalt surface to be suitable for aerial calibration requires that its directional reflectance properties should be close to isotropic. This suitability was tested by measuring the bidirectional reflectance factor (BRF) of nine asphalt samples. The asphalt samples were selected so that their ages and wear levels varied from recently laid surfaces to ones that were several years old and had lost most their binding material. Two control targets, a concrete slab and a sandy surface sample, were measured for comparison.

The measurements were carried out using Finnish Geodetic Institute's Field Goniospectrometer (FIGIFIGO) [35]. FIGIFIGO is capable of measuring the BRF covering a wavelength range of 350 nm to 2500 nm from the hemisphere surrounding a target of interest.

The measurements showed that the aging and wearing of asphalt surfaces causes their directional reflectance to brighten up as the angle of the observation increases. Especially the direct backscatter direction was significantly brightened up. On the other hand, freshly-laid asphalt surfaces were observed to scatter light efficiently in the front direction while reflections to their sides and back remained negligible. Overall, the conclusion drawn from the results was that the reflective properties of the asphalt surfaces were not stable enough to be used directly as quantitative gray scale calibration targets for aerial images.

However, the results also showed that if the observation angle to the surface was below 20 degrees, then the reflectance value changes stayed within a few percentage points of the measured nadir reflectance. This minor change would allow using asphalt surfaces in tentative calibrations or in applications where greater radiometric tolerances are acceptable.

The most pronounced directional reflectance effects were observed either in the direct back and front directions in all of the studied cases. This result can be used when planning new airborne campaigns as selecting the flight lines parallel to the principal plane of illumination would minimize the reflectance brightening sideways.

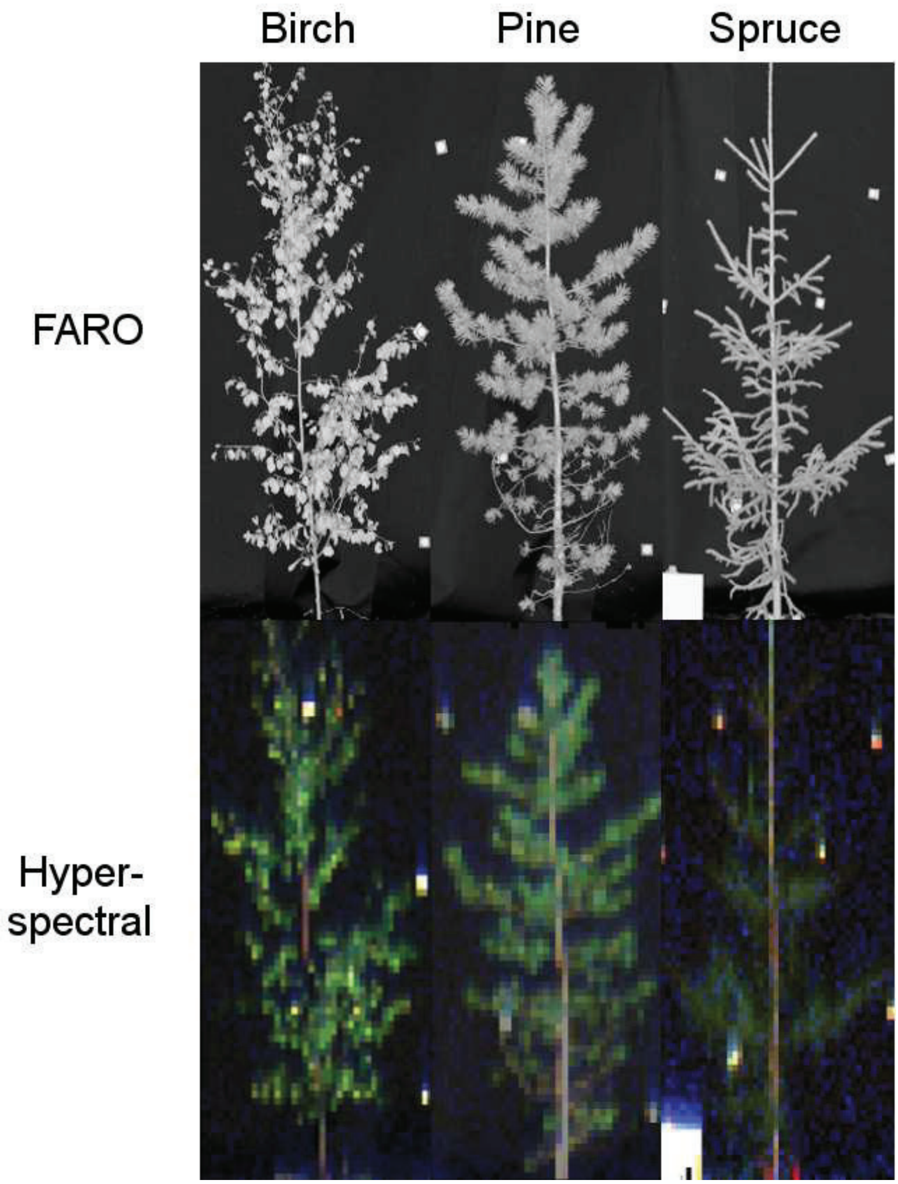

Figure 4.3: *Upper row*) LiDAR intensity of the examined tree species. *Lower row*) Actively scanned hyperspectral images of the examined tree species. The white dots and the large rectangle are the reference targets used in data registration and calibration.

Chapter 5

Discussion

5.1 The Main Goal of the Dissertation and the Results

The main goal of this dissertation was to study and develop new methods for individual tree species classification. The research and analysis efforts focused on using combined spectral and point cloud data. The data collection was performed using different measurement systems and with different collection geometries. Spectral data were collected using both active and passive sensors. In two of the studies, namely in Study **II** and in Study **III**, data were collected with measurement systems that are pioneering ones in the field of forestry.

This dissertation focuses on two main results.

The first result is that the use of actively-collected multi- and hyperspectral laser data has a significant potential for improving the outcomes of tree species classification studies at the individual tree level. A combination of spectral and spatial data yielded the best classification results in all three classification experiments. From the technical point of view, active spectral scanning eliminates most of the dependencies on the external lighting conditions. Thus, radiometric calibration becomes more realizable. Another equally important aspect in a system that integrates the collection of spectral and spatial data is that there is no need to combine datasets from separate sensors. Data combination is a process that often requires considerable amount of time and resources.

Moreover, data combination processes have their limitations, which further limit their usability. An EuroSDR registration quality report presents a comprehensive review of the performance of different registration methods between LiDAR data and imagery [144]. The registration performances of fourteen different registration methods were tested in the report. The data were collected in a built-up environment. The report showed that methods utilising 2D- or 3D-feature extraction from imagery resulted in planimetric errors. The errors were of similar size to those obtained from a registered 3D point cloud. The report also states that the level of automation had no significant effect on registration quality, which depended more on the selected implementation method and tie-point types.

The second result is that overall tree species classification accuracies of over 80% can be achieved. Moreover, relatively few classification features are required when the features are selected from both spectral and spatial domains. Similar results were obtained in two experiments where the data were collected either fully (Study **II**) or partly (Study **III**) using experimental equipment. This implies that it is possible to classify tree species with over 80% overall classification percentage even when the available data resolution is not at the level of specialized state-of-the-art sensors. Thus, the result further promotes the usability aspect of an integrated, multiple-channel, active scanner system. However, the results have their limitations due to new study concepts and instrumentation. The dataset sizes were limited from the statistical point of view in both studies. Also, the classification approach, one-against-all, is computationally demanding and susceptible to overfitting. Therefore, the results and their limitations need to be studied further before making any far-reaching conclusions about general study cases or operational use.

In addition to the above two main results, the experiments yielded the following findings:

The effect of classification feature selection on the obtained classification results was tested extensively in Study **II**. The best results were obtained by testing the feature quadruples formed from the best-performing feature pairs of 123 spectral features and of 34 spatial features. However, the straight-forward selection of the classification features were reported to produce the close-to-best classification accuracy. The result adds to the applicability of combined data as it implies that sufficient classification accuracy can be obtained efficiently when using large feature sets. Alternatively, it should also be possible to build measurement systems for specific operational purposes when a suitable feature set is already known. However, proper validation routines need to be planned and tested before an operative level can be reached.

Spatial classification features were found to give better classification performance than spectral classification features when the classification features were selected from one domain. The main reason for this was in the passive collection of spectral data in outdoor studies. Passive data collection added significant variance in the data as directional lighting effects and shading from surroundings could not be fully corrected with radiometric calibration. However, in Study **III**, which was conducted in laboratory conditions, the classification performance of actively-collected spectral features was almost on par with the spatial features. The result shows effectively how external conditions have a major impact on passively collected data and why vicarious radiometric calibration is of such great importance. But in practice, performance of proper calibration has its difficulties as Studies **II** and **IV** show: close-to-ground measurements with a large horizontal viewing component are prone to the effects of directional lighting and shading if the measurement system does not carry an active light source of its own.

5.2 Comparison with Other Studies Using Combined Laser Scanning and Spectral Image Data in Forestry

Combined spectral and spatial data for remote sensing and forestry research have been studied extensively over the past two decades. Comprehensive reviews of more recent studies have been written by Koch and by Wang *et al.* [145, 146]. Most of the earlier studies were performed using airborne equipment mounted on airplanes or on helicopters. Contrary to this, three out of the four studies presented in this dissertation were carried out at ground level, which meant using completely different, horizontal, data collection geometry. Moreover, the classification data in two of the studies were collected using novel sensor systems. These aspects make direct result comparisons between different studies difficult.

Difficulties in direct result comparisons between different classification methods are a more general issue. Results are usually reported for specific data, whose collection technique, time of collection, density, and resolution all differ from each other. Moreover, the number and types of classified targets are also different and classifications are performed with various algorithms. In addition, there are very few comparison studies where the same data have been analyzed using different methods.

An EuroSDR forestry study for common forestry parameter extraction by Kaartinen and Hyyppä was one of the comparison studies [131]. The study showed that there was significant variance in the performance of twelve tested extraction algorithms. One of the main conclusions of the study was that the previous performance of a forest parameter extraction algorithm in its development environment cannot be taken directly as a reference when the algorithm is applied to a different dataset.

With the previous reasoning in mind, it is not feasible to make a quantitative comparison of study results obtained in Studies **I - III** with other classification studies. However, the results can be assessed on a qualitative level. Study **I**, whose data were collected with airborne sensors, utilized LiDAR-derived DSM to separate illuminated and shaded tree crown parts and to use the spectra of the separate sides for tree species classification. The best overall classification accuracy was obtained with combined data and it was 74.5% for 295 individual trees representing three Nordic tree genera and species. The result is in line with the results of other studies using aerial imagery and/or LiDAR data. Korpela *et al.* reported classification accuracies of 61.1% to 78.9% at stand-level in data collected from Nordic forests [116]. They classified four forest classes using at maximum of eight features at a time. They used combined aerial imagery and LiDAR data in the classification. In their other study [147], they applied anisotropic properties of tree canopies and were able to classify three tree species with a classification accuracy as high as 80% for data collected from the height of 3 km to 4 km. On the other hand, Persson *et al.* classified the same three tree species with over 90% accuracy when they used high resolution aerial imagery and LiDAR data [123]. However, their method did not perform with the same efficiency with lower resolution data when the method was used as a reference in Study **I**. In more temperate regions, classification accuracies of 84% for four tree classes have been reported by Heinzel *et al.* [124]. Additionally, Waser *et al.* have reported of an overall classification result of 86% for five tree species [122].

In land class studies, Bork and Su have obtained classification accuracies of 91.0% and 80.3% for three and eight vegetation classes consisting of trees and low vegetation [111]. Their classification was done unsing integrated airborne LiDAR and multispectral imagery data. Koukoulas and Blackburn detected 80% of the trees of a semi-natural study forest using a height model created from ALS data and multispectral imagery [117]. Dalponte *et al.* reported classification accuracies of over 85% for dominant land classes in a study applying hyperspectral and ALS data [112]. Asner *et al.* used combined airborne imaging spectroscopy and LiDAR to detect the fractional abundance of three invasive species in Hawaiian rainforests [110]. They reported error rates of less than 6.8% and 18.6% with minimum canopy cover thresholds of about 7 m^2 and 2 m^2.

The results of Study **II** show that the fusion of MLS and hyperspectral spectrometer data has the similar level of classification performance as has been reported in the literature. The results can be considered to be good. Lighting conditions during the data collection were challenging, only a few classification features were used in classification, and ten different species were classified. Moreover, the data were collected using a prototype system.

Study **III** produced even better results, but the data collection was performed in laboratory conditions. Thus, the results of Study **III** should be considered as a close-to-best case scenario of obtainable classification accuracies that could be achieved when most external factors are negated in the data. However, the results of Study **III** could gain additional improvement from the utilization of directional lighting information.

5.3 Future Research

Three different study cases about the classification of individual tree species with combined spectral and spatial data have been presented in this dissertation. In addition, one study focused on radiometric calibration from man-made surfaces. Based on the results of all these four studies, it is possible to draw the following conclusions about data collection and processing in individual tree species classification.

Photogrammetric methods and laser scanning are two well-established data collection techniques and they are used extensively in forestry research. Photogrammetric methods have been applied successfully for close to a century to provide accurate data over large areas. Laser scanning emerged two decades ago, and it has developed into a well-established technique that can be utilized to extract accurate forestry data. However, both techniques have their limitations. These limitations can be compensated for many cases by using data collected using the other technique. Thus, the next logical step is to further improve data collection. Improvement can be achieved by increasing the level of integration between the two techniques. The dissertation's results clearly suggest that *development of new laser scanner systems capable of active ranging in multiple wavelength channels or spectral bands should be encouraged*. The classification accuracy of combined data outperformed single-sensor data in all of the three classification studies by a significant margin. In addition to improved classification accuracy, active multiple-channel scanners enable efficient and time-independent data collection from different viewing geometries. Active scanner systems are resilient to external lighting conditions and their changes. The possibility for time-independent measurements has especially great potential as it allows diurnal change monitoring of trees and other vegetation. However, proper radiometric calibration processes need still to be developed to guarantee compatibility between different measurements.

The dissertation results also give some implications on how actively scanned multiple-channel data should be processed. First of all, both Studies **II** and **III** reported that the spatial features derived originally for area-based ALS studies could be transferred almost directly to horizontal viewing geometry. Moreover, the classification performance of the spatial features was better than that of the spectral features. Another important finding was that the total number of classification features needed could be kept low when using combined data. The low total number of combined classification features implies that the tested feature collection and matching techniques could be applied at the operative level in areas with a few dominant species once instrumentation is developed enough. In temperate regions, the number of significant species is over ten or more and additional features will be needed to enable accurate species discrimination. The number of possible classification feature combinations grows as a factor of the number of classification features. Therefore, efficient feature screening methods have to be used to determine close-to optimal feature sets for each application if no *a priori* information is available. Also, data collection for operative purposes requires that the methods can be transferred back to the airborne configuration, which is the most cost-efficient way at present for collecting combined data over large areas. Optimally, future forestry inventories will be conducted so that reference data are collected using terrestrial and mobile platforms. The reference data are then used in training classifiers for tree parameter discrimination from airborne data.

Thus, a possible approach regarding further development of the first active multi-wavelength scanner systems is first to emphasize their spatial data collection properties, i.e. resolution and scanning speed. The number of detected wavelengths could be limited only to those specifically needed in an application. Such a solution should offer a relatively fast way for the development of new systems that possess the required performance for operative use. The lack of raw performance has been seen as the main concern regarding the operational use of multi-wavelength laser scanners [2].

High resolution spatial data with a few wavelengths have also another benefit in addition to their fast applicability. A few narrow wavelength bands enable better control over the operational transmitter powers than when using a wide spectral range. This is important from the safety perspective. It is of high importance that the transmitter powers of new multi-wavelength scanner systems are kept below the national safety regulation limits. The limits have to be passed so that a scanner system can be deployed for field work. A few specifically selected wavelengths or bands also offer one other advantage. Instrumentation with high sampling rates is easier to obtain with a few receiver channels than with a full spectrum because then less processing is required.

New multi-wavelength scanner systems can be expected to emerge in the next few years. While they will provide increasingly accurate information on their surroundings, this also means that the size of the collected datasets will significantly increase. The data increase introduces an additional burden on data processing. Thus, data processing should be given more consideration already during development of new measurement systems. This would enable early implementation of possible filter schema already in the preprocessing phase. Similar issues are already present to some extent in TLS studies. For example, a single-scan TLS study can contain tens of millions of individual single-wavelength laser points. The point number in itself presents a challenge when data from several scans are co-registered together [148]. Furthermore, a large proportion of data collected in close-to-ground measurements comes from ground hits in the vicinity of the scanner. This leads to high level of redundancy in the ground hits. One possible solution to reducing data has been presented in a terrestrial laser scanning case: Litkey *et al.* have suggested performing distance-based selective sampling on collected point clouds to retain hits coming from distance and to significantly reduce the number of close hits [149].

This dissertation's results have also given a rise to new research questions in addition to the improvement suggestions considering instrumentation and data processing. The new research topics include methods for further improving tree species classification, comparison studies with earlier classification experiments, and measurement and development of completely new forestry parameters. New forest parameters should utilize fully simultaneously collected spatial and spectral information. These new parameters could provide more accurate information at tree and at sub-tree level. Improved information could be obtained, for example, about trees' branch distribution and biomass [145, 150, 151].

Chapter 6

Summary

Remote sensing is an efficient means of collecting forest data. The data thus collected can be used to calculate estimates for other important parameters of interest, e.g. biomass, stem number, and carbon exchange. Tree species information can be used to further improve these estimates. Thus, tree species determination, especially at the level of individual trees, is of high interest for a wide variety of both scientific and commercial applications. Therefore, novel methods are needed to achieve improved tree species classification performance with a high level of automatization.

One approach towards improving the tree species classification performance is to further develop already existing remote sensing techniques, namely laser scanning and spectral imagery. These techniques have provided a solid basis for current operative forest inventories. However, both laser scanning and spectral imagery have their inherent limitations. Laser scanning data is limited to a very narrow spectral region and its radiometric properties are often obscured. On the other hand, while range information collection from spectral imagery is possible, it requires highly specialized processing techniques and dense coverage. Moreover, spectral imagery are collected with passive techniques, which makes them susceptible to the effects of environmental lighting. These limitations can be adressed to some extent through improved instrumentation and data processing methods, but this approach becomes increasingly difficult in terms of cost efficiency over extended periods of time.

As laser scanner data and spectral imagery complement one another's limitations, data fusion between them has been shown to yield accurate results in forestry studies. However, data fusion presents new challenges that need to be accounted for before data fusion can be fully utilized. The new challenge comes from data registration between the two data types. Registration can be particularly difficult if the data are collected during separate measurements. Data fusion also results in large datasets that present yet another challenge. Their efficient processing is demanding unless the amount of data can be limited.

The focus in this dissertation is on studying how data from these two sources of data can be collected, combined, and analyzed effectively in order to improve tree species classification. Four separate studies were carried out to achieve this goal. Each study concentrated on different properties of data fusion when dealing with remote sensing data. Three of the studies used classification features extracted from the data to classify different tree species. The three studies were carried out using different sensor systems that included a novel actively-scanning hyperspectral laser scanner and a novel mobile platform capable of covering vast road-side areas. The fourth study experimented with the subject of whether the directional lighting effects in passively collected spectral data could be calibrated using man-made surfaces as references.

The results of the studies showed that actively-collected hyperspectral data have a significant potential in tree species classification. The classification results were best results when the classification features were selected from both spatial and spectral data. One study also implied that mixed classification feature selection can yield relatively high results even when the fused data are collected using an experimental instrument, whose absolute resolution is lower than that of the commercial state-of-the-art sensors. Furthermore, two studies also showed that it is possible to transfer spatial feature extraction methods, originally developed for airborne remote sensing data, into horizontal scanning geometry.

The results are promising considering future research as they imply that already-established data processing methods can be exploited in horizontal viewing geometry. However, even though similar data analysis methods seem to work also in horizontal viewing geometry, one should not make direct comparison between the results from airborne and terrestrial point cloud data as more in-depth comparison experiments have to be carried out. Further investigation is also required in order to determine new classification features describing object shape and spectrum simultaneously. The new features can be collected by using active hyperspectral measurements.

The dissertation addresses the possibilities of using combined remote sensing data that contain both spatial and spectral information for a particular forestry application, i.e. tree species classification. However, there should be no limitations to apply similar types of data and data analysis techniques in other remote sensing applications, be they of environmental or urban nature. Different applications concentrate on different characteristic features, but most of them are likely to benefit from simultaneously collected, high resolution, spatial and spectral data.

All in all, a potential breakthrough in remote sensing is very likely to happen within the next ten years. New active multi- and hyperspectral laser scanning techniques have been presented in recent years in increasing numbers. The potential of these techniques is significant as they offer convenient means of simultaneously collecting combined spatial and spectral data. Thus, they would remove several intermediate data processing steps and diminish the effect of diffuse lighting. The new techniques could enable high signal-to-noise ratios with low contributions from external factors.

Another notable development in remote sensing instrumentation is going on in mobile and terrestrial laser scanning. New laser scanning systems are more light-weight and compact than previous models and they can be mounted on a wide variety of platforms. Laser scanner systems mounted on small aerial, marine, and land-based vehicles offer agile and responsive means of collecting accurate spatial data from areas of interest within narrow time windows. Eventually, after new laser scanning techniques have evolved enough, they can gradually replace manual data collection in several fields of study.

Considering all the ongoing development and changes in data collection techniques, one should bear in mind that new data processing techniques are also needed for transferring the essential, application-specific, information to end-users. It is a matter of importance to prevent method fragmentation into platform-restricted solutions and thereby enable the adaptation of new techniques as soon as possible for a wide range of applications.

Nonetheless, the next several years will witness interesting developments in the field of close-range remote sensing.

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