

Novel algorithms for efficiently
accumulating, analysing and
visualising full-waveform LiDAR in
a volumetric representation with
applications to forestry

submitted by

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Milto Miltiadou

Abstract

no more than 300 words

NOTES:

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Purple colour: addition/corrections according to Mike's comments

Red colour: notes

Gray colour: text that is going to be modified

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Abstract

This study focuses on enhancing the visualisations and classifications of forested areas using coincident full-waveform (fw) LiDAR data and hyperspectral images. The ultimate aim is use both datasets to derive information about forests and show the results on a 3D virtual, interactive environment. Influenced by Persson et al (2005), voxelisation is an integral part of this research. The intensity profile of each full-waveform pulse is accumulated into a voxel array, building up a 3D density volume. The correlation between multiple pulses into a voxel representation produces a more accurate representation, which confers greater noise resistance and it further opens up possibilities of vertical interpretation of the data. The 3D density volume is then aligned with the hyperspectral images using a 2D grid similar to Warren et al (2014) and both datasets are used in visualisations and classifications.

Previous work in visualising fw LiDAR has used transparent objects and point clouds, while the output of this system is a coloured 3D-polygon representation, showing well-separated structures such as individual trees and greenhouses. The 3D density volume, generated from the fw LiDAR data, is polygonised using functional representation of object (FReps) and the marching cubes algorithm (Pasko and Savchenko, 1994) (Lorensen and Cline, 1987). Further, an optimisation algorithm is introduced that uses integral volumes (Crow, 1984) to speed up the process of polygonising the volume. This optimisation approach not only works on non-manifold object, but also a speed up of up to 51% was achieved. The polygon representation is also textured by projecting the hyperspectral images into the mesh. In addition, the output is suitable for direct rendering with commodity 3D-accelerated hardware, allowing smooth visualisation.

In future work, the effects of combining both hyperspectral imagery and fw LiDAR in classifications and visualisations are examined. At first, two pixel wise classifiers, a support vector machine and a Bayesian probabilistic model, will be used for testing the effects of the combination in generating tree coverage maps. Higher accuracy classification results are expected when metrics from both datasets are used together. Regarding the visualisations, the differences of applying surface reconstruction versus direct volumetric rendering will be discussed and an ordered tree structure with integral sums of the node values will be used for speeding up the ray-tracing of direct volumetric rendering and improving memory management of aforementioned optimisation algorithm with integral volumes. Further, deferred rendering is suggested for testing the visual human perception of projecting multiple bands of the hyperspectral images on the FW LiDAR

polygon representations. At the end of this project the combination of the datasets will be used along with the watershed algorithm for tree segmentation, which is useful for measuring the stem density of a forest and for tree species classifications.

from EDE:

Firstly, a new and fast way of aligning the FW LiDAR with Remotely Sensed Images has been developed in DASOS and by generating tree coverage maps it was shown that the combination of those datasets confers better remote survey results. This work was presented at the 36th ISRSE International Conference.

Secondly, automated detection of dead trees in native Australian forests has a significant role in protecting animals, which live in those trees and are close to extinction. DASOS allow the generation of 3D signatures characterising dead trees. A comparison between the discrete and FW LiDAR is performed to demonstrate the increased survey accuracy obtained when the FW LiDAR are used.

Finally, the last application is for improving visualisations for foresters. Foresters have a great knowledge about forests and can derive a wealth of information directly from visualisations of the remotely sensed data. This reduces the travelling time and cost of getting into the forests. This research optimises visualisations by using the new FW LiDAR representations and a speed of up to 51% has been achieved.

FW LiDAR has great potentials in forestry and this research has already started to have an impact in the FW LiDAR community by making those huge datasets easier to handle. DASOS is now used at Interpine Group Ltd, a world leading Forestry Company in New Zealand and it has been tested from a PhD student at Bournemouth University who looks into estimating bird distribution in the New Forest. In the future, it is expected that DASOS will be widely used in remote forest surveys (i.e. estimating the commercial value of a forest and detecting infected trees at early stages for treatment).

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Abbreviations and Glossary

AGC	Automatic Gain Controller
ALS	Airborne Laser Scanning
APL	Airborne Processing Library
ARF	Airborne Research Facility
CG	Computer Graphics
CHM	Canopy Height Model
CUDA	parallel computing platform available on nvidia graphic cards
DASOS	(δασος=forest in Greek), the open source software implemented for managing FW LiDAR data
DBH	Diameter at Breast Height
DEM	Digital Elevation Model
DTM	Digital Terrain Model (DTM)
FW	Full-Waveform
GB	Gigabyte
GPU	Graphics Processing Unit
LiDAR	Light Detection And Ranging
MRI	Magnetic Resonance Imaging
NASA	National Aeronautics and Space Administration
NDVI	Normalised Difference Vegetation Index
NERC	Natural Environment Research Council
NIR	Near-Infrared Region of the electromagnetic spectrum
QGIS	Quantum Geographic Information System
SIMD	Single Instruction, Multiple Data
TB	Terabyte
VIS	Visual Spectrum
VLR	Variable Length Records
WPDF	Waveform Packet Descriptor Format
UK	United Kingdom

Publications

DASOS-User Guide, M. Miltiadou, N.D.F Campbell, M. Brown, S.C. Aracil, M.A. Warren, D. Clewley, D.Cosker, and M. Grant, Full-waveform LiDAR workshop at Interpine Group Ltd, Rotorua NZ, 2016

Improving and Optimising Visualisations of full-waveform LiDAR data, M. Miltiadou, M. Brown, N.D.F Campbell, D. Cosker, M. Grant, *EuroGraphics UK, Computer Graphics & Visual Computing*, 2016

University of Bath Alignment of Hyperspectral Imagery and Full-Waveform LiDAR data for visualisation and classification purposes, M. Miltiadou, M. A. Warren, M. Grant, and M. Brown, *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 40, no. 7, p. 1257, 2015.

Reconstruction of a 3D Polygon Representation from Full-Wavefrom LiDAR data, M. Miltiadou, M. Grant, M. Brown, M. Warren, and E. Carolan, *RSPSoc Annual Conference, New Sensors for a Changing World*, 2014.

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EDE and Ravenscroft Prize - Finalist: Selected as one of the five finalists for this is a prestigious prize that recognises the work of best postgraduate researchers.

Student Poster Competition at Silvilaser.

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Remote Sensing Cyprus (RSCy) Conference, 2017 , Paphos, Cyprus - Oral Presentation

ForestSAT Conference,2016 , Santiago, Chile - Oral Presentation

Computer Graphics & Visual Computing (CGVC),2016, Bournemouth, United Kingdom - Poster Presentation

Silvilaser, 2015, La Grant Motte, France - Oral Presentation

International Symposium of Remote Sensing of the Environment (ISRSE), 2015, Berlin, German - Oral Presentation

Remote Sensing and Photogrammetry Society (RSPSoc) Conference, New Sensors for a Changing world , 2014, Aberystwyth, United Kingdom - Oral Presentation

Workshops

Full day workshop about FW LiDAR and DASOS at *Interpine Ltd Group*, 2016,
Rotorua, New Zealand

Demonstration of DASOS_v2 at the practical LiDAR session at *the NERC ARF annual workshop*, 2017, Plymouth, United Kingdom

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Chapter 1

Introduction

1.1 Forest Monitoring: Importance and Applications

1.2 Background Information about Remote Sensing and Airborne Laser Scanning Systems

Remote sensing refers to the acquisition of information about objects, for example vegetation and archaeological monuments, without physical contact and the subsequent interpretation of that information. The sensors used to capture the information are divided into passive and active. For example satellite photography is passive because information are collected from the reflected natural sun light, while Airborne Laser Scanners (ALS) are active because they emit laser beams and collects information from the backscattered laser energy [1].

According to Wanger et al, Airborne Laser Scanning (ALS) is a growing technology used in environmental research to collect information about the Earth, such as vegetation and tree species. Comparing ALS with traditional photography, ALS is not influenced by light and it is therefore less dependent on weather conditions (ie. it collects information from below the clouds, or at night). The laser beam also partially penetrates the tree canopies allowing it to record information about the forest structure below the canopy, as well as the ground [2]. ALS methods are divided into pulse systems, which repeatedly emit pulses, and continuous wavelength systems that continuously emit light. They both acquire information from the backscattered laser intensity over time, but continuous wavelength systems are more complicated because they obtain one extra physical parameter, the frequency of the ranging signal. Further, according to Wehr and Lohr, continuous wavelength systems are 85 times less accurate than pulse systems [3].

LiDAR (Light Detection And Ranging) systems are active and pulse laser scanning systems [3]. They are divided into two groups according to the diameter of the footprint left by the laser beam on the ground, which is primarily dependent on the distance between the sensor and the target (altitude, in most remote sensing) and the beam divergence. The small-footprint group has a 0.2-3m diameter, is widely commercialised and the sensors are mostly carried on planes (ALS systems). In contrast, the large-footprint systems have a wider diameter (10-70m) and during experiments they were mostly mounted on satellites. Small-footprint systems record at higher resolution but cannot guarantee that every pulse will reach the ground due to the small diameter of their footprint, making topographic measurements difficult, and are limited to smaller survey areas due to the cost and availability of aircraft. In contrast, large-footprint scanners have wider diameters and can therefore scan wider areas with the likelihood of recording the ground to be higher [4].

In addition, there are two types of LiDAR data: discrete and full-waveform (FW). Discrete LiDAR records a few peaks of the reflected laser intensity, while FW LiDAR stores the entire backscattered signal. The discrete LiDAR has been widely used and a 40% reduction of fieldwork has been achieved at Interpine Ltd Group, New Zealand, with that technology. Regarding the newer FW LiDAR, scientists understand their concepts and potentials but due to the shortage of available tools able to handle these large datasets, there are very few uses of FW LiDAR [5].

The design of the first FW LiDAR system was introduced in 1980s, but the first operational system was developed by NASA in 1999 [6]. The vastly increased amount of information recorded within the FW LiDAR suggests many new possibilities and problems from the point of view of image understanding, remote surveying and visualisation. As an indication, a 9.3GB discrete LiDAR from New Forest, UK, corresponds to 55.7GB of FW LiDAR.

This research is focused on the representation and efficient use of FW LiDAR data and contributes both to forestry visualisations and classifications. Two datasets are used for testing and evaluation: the New Forest and the RedGum dataset. An in-depth explanation of LiDAR systems and the specifications, differences and challenges of the two datasets are given in Section 2. An overview of the specific aims, objectives and contributions of this thesis, set in the context of these datasets, is then given at Section 3.

Chapter 2

Acquire Data

The aim of this section is to give a practical and scientific insight into the acquisition of data, because a good knowledge of these methods and their limitations is essential for understanding the related research undertaken. The relations between the two main datasets used in this project are depicted on Figure 2-1 and briefly explained here:

- The **New Forest dataset** from the UK was provided by the Natural Environment Research Council's Airborne Research Facility (NERC ARF). Measurements were collected simultaneously a Leica ALS50-II LiDAR and AISA Eagle/Hawk hyperspectral radiometers on the 8th of April in 2010. It contains Discrete LiDAR, FW LiDAR and hyperspectral images.
- The **RedGum dataset** was acquired in Australia using a Trimble AX60 integrated LiDAR/Camera instrument over the time period from the 6th of March in 2015 until the 31st of March in 2015. It was provided by the RPS Australia East Pty Ltd. Only the FW LiDAR data are used here.

The ALS data are explained first, because they are the main focus of this research, and hyperspectral imagery is towards the end of the chapter. In Section 2.1, an in-depth description of ALS systems and the differences between discrete and FW LiDAR data is given. Section 2.2 briefly discusses the binary file format of the acquired LiDAR data and Section 2.3 is a discussion on the limitations, the differences and the advantages of two LiDAR instruments; the Leica and Trimble. The essential information about the hyperspectral imagery, which is only associated with the New Forest dataset, is then covered in Section 2.4.

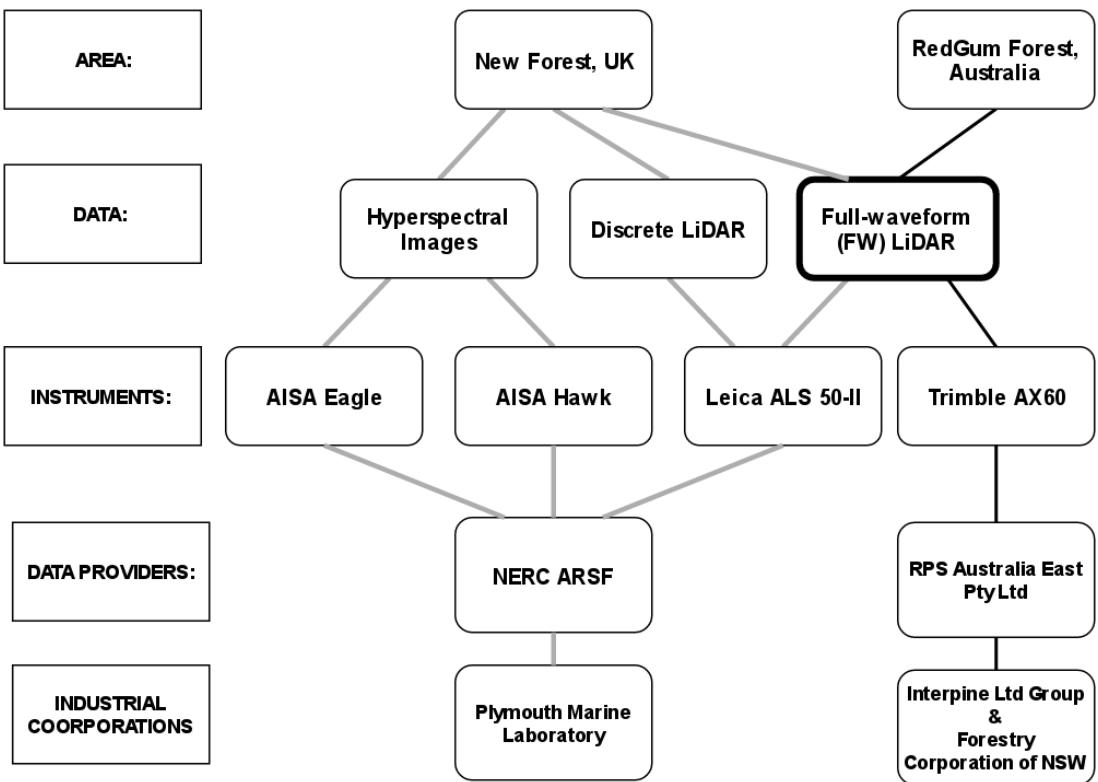


Figure 2-1: Data and Instruments

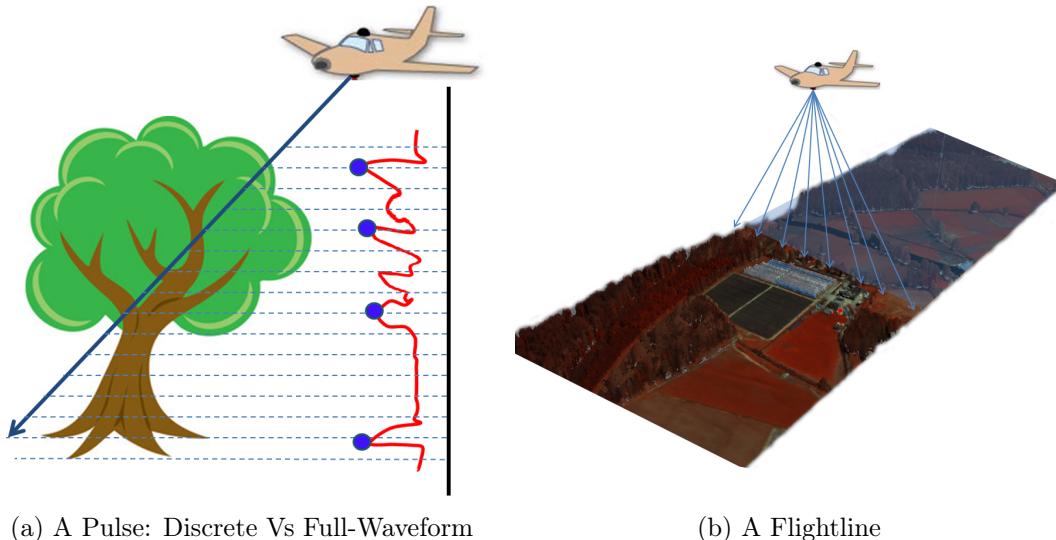


Figure 2-2: Airborne Laser Scanning System

2.1 Airborne LiDAR systems: An in-depth Explanation

The ALS systems emit laser pulses from sensor mounted in a plane and collects information from the time-of-flight and the returned laser intensity. By the time the pulse has travelled the approximately 1-3km from the aircraft to the ground, it is roughly 20cm in width due to beam divergence. When the pulse hits an object (e.g. the forest canopy), then some of it reflects back while the rest penetrates through holes between leaves and branches. The laser pulse continues to hit structures, scattering and partially returning to the sensor until it reaches a solid barrier such as the ground and is fully blocked from further progress. The LiDAR systems record information from the backscattered laser pulse, measuring its round trip time and the returned intensity.

As mentioned at Section 1.2, there are two types of LiDAR data, discrete and FW. The discrete LiDAR observes the returned intensity signals and identifies and [records a few peak intensity returns of the signal](#), while the FW LiDAR system digitises and stores the entire backscattered signal into equally spaced time intervals (Figure 2-2a). The delivered data for the discrete LiDAR is a set of hit points ("returns"), which are associated with laser intensities. The world position of every return is calculated by measuring the round trip time of the laser return, giving a distance from the sensor, which is combined with the precisely known position and orientation of the aircraft/sensor (from GPS, an inertial measurement unit and precise shot direction of the laser pulse). The waveform recordings are triggered by and attached to first returns of discrete LiDAR data (to avoid sampling the uninteresting time period while the pulse travels through the atmosphere) and they are a list of intensities that correspond to the laser intensity returned over time. There is also an offset vector which defines the distance and direction between each wave sample (effectively a compression mechanism, by avoid recording the world position of every sample, replacing it with the location of the first return and this vector).

As shown in Figure 2-2b, the pulses are scanned back and forth across the landscape below (by a rotating mirror) as the plane travels forward. The scanned data has a limited maximum width according to the flight height and the field of view scan angle. During processing the track of the plane is divided into easier-to-handle pieces (flightlines) and saved into separate binary files. In this project the LAS1.3 file format is used for both datasets.

2.2 Brief Description of the LAS1.3 File Format

There are a few LiDAR file formats but the LAS1.3 was the first format to contain FW data and it is the one used to store the data for both New Forest and RedGum datasets. According to the LAS1.3 file specifications [7], a .LAS file contains information about both discrete and FW LiDAR data, with the waveform packets attached to discrete returns and saved either internally at the end of the .LAS file or externally in a .WVS file.

As shown at (Figure 2-3) the .LAS file is divided into four sections and a brief explanation of each section is given here:

1. The **Header** contains general information about the entire flightline. For example, it includes the maximum scan angle used during the flight, whether the waveform packets are recorded internally or externally and the number of **Variable Length Records** (VLR).
2. Regarding the **VLR**, which contain arbitrary "extension" data blocks, the most important information given is the waveform packet descriptors that contain essential information on how to read the waveform packets (i.e. an ID, the number of wave samples and the size of each intensity in bits).
3. The **Point Data Records** are the discrete points and the waveforms are associated with first return discrete points. Each Point Data Record has a spatial location, an intensity and optionally a pointer to a waveform packet as well as the ID of the corresponding waveform packet descriptor.
4. The waveform packets is a list of intensities and they are either saved internally into the **Extended Variable Length Records** section of the .LAS file or inside an external .WVS file. Starting from the associated first return point, the spatial locations of the waveform packet (wave sample intensity) are calculated by adding an offset defined in the associated Point Data Record.

2.3 Leica Vs Trimble Instruments: Limitations, Differences and Advantages

As shown in Figure 2-1, the Leica ALS 50-II instrument was used to capture the LiDAR data of New Forest dataset and the Trimble AX60 for collecting the RedGum Forest FW LiDAR data. It is therefore important to clarify the differences, the limitations and the advantages of each instrument.

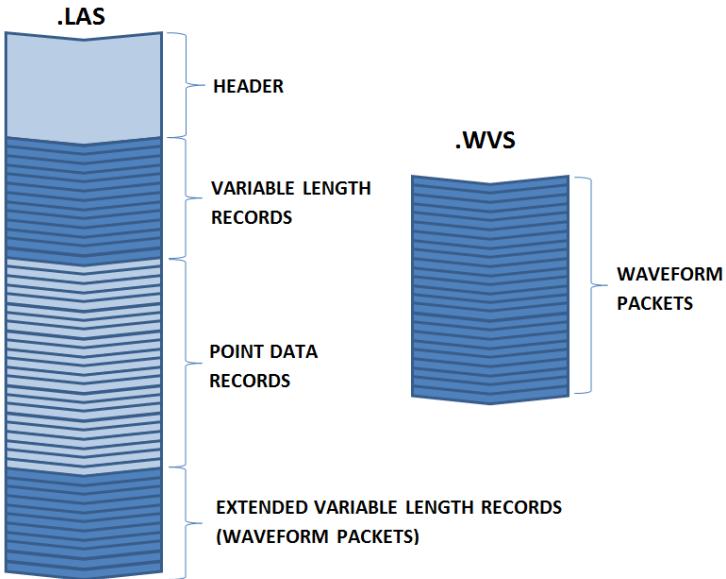


Figure 2-3: How the FW LiDAR data are stored into a binary file, according to the LAS1.3 file format specification

The Trimble performs at a pulse frequency of 400kHz, while the Leica's maximum pulse frequency is 120kHz. Nevertheless, during experiments there were occasions when the Leica discarded every other waveform due to I/O limitations despite being at or below the maximum pulse frequency [8]. The New Forest dataset has been affected by this and, on average, one third of the saved pulses only contain discrete data. We should therefore be extremely careful when comparing Discrete with FW LiDAR data. While [5] concludes that FW LiDAR data worth the extra processing because they have a better vertical profile, [9] states that extra information (the echo-width) from the FW LiDAR data are relatively unimportant. But the New Forest datasets were used for the comparison at [9] and there is no mention about the significantly less waveforms recorded in comparison to the discrete data. It is therefore suspected that their results has been affected by the missing waveforms.

Another problem with the Leica sysyem is the small dynamic range of intensities due to the number of bits used for recording them; the Leica system uses 8-bit integers (0-255 range) while the Trimble uses 16-bit integers (0-16385 range). For increased dynamic range and finer intensities without doubling storage costs, Leica introduced an Automatic Gain Controller (AGC). The AGC is an 8-bit number that defines how the recorded intensity range is shifted across a wider range of intensities. The AGC value is adjusted according to the reflected laser intensity of the previous 64 pulses and it therefore varies across a flightline. Consequently, the raw intensities are incomparable

to each other and, since the relation between AGC and the intensities is not linear, the range normalisation is complicated [10] [11]. In this thesis, the intensities of the Leica system are used as boolean values (whether something existed or not, using a user-defined threshold) to quickly overcome that issue and focus on the major research objectives. Regarding the Trimble instrument, there is no AGC value because the intensities are saved into a 16bit integer and as long as the flight height is constant no normalisation is required. In a few words, the raw intensities recorded using the Leica system are not normalised and therefore not comparable to each other, while the intensities of the Trimble instrument are more meaningful.

The footprint of the laser on the ground depends on the scanning pattern of the instruments and the field of view. The sinusoidal scanning pattern of the Leica system results in a higher density of returns at the edges of the flightline. The footprint of the Trimble instrument is more equally spaced because they are scanned using a rotating polygon. The uneven density pattern of the Leica system is resolved by normalisation during the voxelisation process, but the Trimble's equally spaced pulse pattern is more prone to aliasing when voxelised. Regarding the field of view, the Leica is wider but both systems avoid large angles because otherwise data look deformed at edges of the flightlines.

Last but not least, the Trimble instrument is a native full-waveform sensor; the discrete LiDAR are produced by extracting peak points in post-processing. Therefore one of the purported advantages of a FW system, the concept of extracting a denser point clouds using Gaussian decomposition [2], does not apply in the Trimble's case. This was proven by extracting peak points from Trimble FW LiDAR data using the pulseextract from LAStools [12]; the number of points extracted was exactly the same as the number of points saved into the associated discrete LiDAR files. Therefore discrete data from the Trimble instrument are the same as those generated by echo decomposition and peak points extraction from the FW samples.

To sum up, the Trimble AX60 instrument is a newer sensor and therefore has less problems or design compromises in comparison to the Leica ALS50-II instrument. Table 2.1 summarises the differences between the two sensors.

2.4 Hyperspectral Imagery

Hyperspectral imagery has a positive impact in remote sensing because it contains information beyond human visibility. The human eye receives light from the visual spectrum into three bands (red, green and blue). The hyperspectral sensors captures a larger spectrum and divides its light components into hundreds of bands, recording

Table 2.1: Specifications of the LiDAR instruments used

Instrument Name:	Leica ALS550-II	Trimble Ax60
Scanned Area	New Forest, UK	RedGum, Australia
Year of Introduction:	Discrete LiDAR 2009 & FW LiDAR 2010	2013
Max Scan Frequency (kHz):	120	400
Recorded Intensity (bits):	8	16
AGC:	Yes	No
Scanning Pattern:	Sinusoidal	The footprints are more equally spaced on the ground
Max field of view (degrees):	75	60

this way more information than a human eye can receive [1].

Nevertheless, there are other compromises - for example, the time taken to integrate incoming light as the aircraft carrying the sensors moves. This means the raw airborne images appear deformed because the pixel length varies across the flightline. NERC-ARF geo-corrects the data using the Airborne Processing Library (APL) [13]. The processing levels are numbered. At ‘level 3’ (world coordinate system) the pixels are equally spaced and sized, which requires resampling and thus may look slightly blurred. The ‘level 1’ data (what the sensor saw) are non geo-corrected but they are associated with a file that defines the spatial location of each pixel. In this thesis, the ‘level 1’ data are used to preserve the highest possible quality.

In practise, the level 1 data are held in two files, the ‘.bil’ and the ‘.igm’. The ‘.bil’ file contains the hyperspectral cube (Figure 2-4), all the pixel values at different wavelengths, and the .igm file gives the x, y, z coordinates of each pixel.

The number of bands and the spectrum range captured depends on the hyperspectral sensor. The data from New Forest were collected using the following instruments:

- the Eagle, which captures the visible and near infra-red spectrum (400-970nm)
- the Hawk, which covers short wave infra-red wavelengths (970-2450nm)

Both sensors divide their spectral range into 252 bands (programmable) and each band is a 2D vector as shown in Figure 2-4).

The hyperspectral images also come with a number of drawbacks. A few are mentioned here but since hyperspectral imagery is not the main focus of the thesis there are not addressed:

- System faults sometimes occurs and the affected areas are masked out. This results in blank areas.

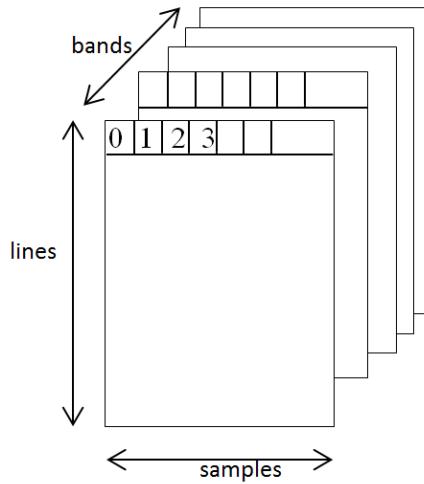


Figure 2-4: This figure shows the order of the hyperspectral pixels saved into the the binary .bil file.

- As a passive sensor, it is dependent on the sun for illumination and thus vulnerable to poor weather conditions
- Due to the high refraction of light at some wavelengths, some bands are highly influenced by humidity (i.e. wavelength 1898.33nm).

To sum up, hyperpsectral images contain information beyond the visible and they are delivered in two files, one contains the hyperspectral cube and the other one the geo-locations of each pixel. In this project, they are used in chapter (Chapter 7), where it is shown that the combination of Remote Sensing data confers better results for generating tree coverage maps.

Chapter 3

Overview of Thesis

Chapter 4

The open source software DASOS and the Voxelisation Approach

As mentioned in Section ??, there are very few uses of FW LiDAR data because of the quantity of the recorded information. For that reason, DASOS was developed (Section 4.3) as an open source software, to help foresters without computer science background to use FW LiDAR data while simultaneously advancing the research goals of this thesis. In this section:

- An overview of related software packages is given and we explain how DASOS differs from those packages (Section 4.1).
- The main method of interpreting the data within DASOS (the voxelisation approach) is described (Subsection 4.2).
- All the functionalities of DASOS are listed (Section 4.3)
- and, finally, a summary is provided (Section 4.4).

4.1 State-of-Art FW LiDAR Software Packages

The most common approach for interpreting FW LiDAR is the Gaussian decomposition of the waveforms for peak-points extraction. Each waveform is modelled as a set of Gaussian pulses and for every Gaussian peak, a single return (equivalent to a discrete LiDAR point) is extracted [14]. Neunschwander et al used this approach for Landcover classification [15] while Reitberger et al applied it for distinguishing deciduous trees from coniferous trees [16]. Chauve et al further proposed an approach of improving the Gaussian model in order to increase the density of the points extracted from the

data and consequently improve point based classifications of FW LiDAR data [6]. The following tools are able to extract discrete points from the waveforms and visualise small areas of interest:

- **Pulsewaves**: visualises a small number of waveforms using different transparencies according to the intensities of the wave-samples and is able to generate discrete point clouds [17].

Link: <<https://rapidlasso.com/pulsewaves/>>

- **FullAnalyze**: supports echo decomposition. Regarding visualisations, the user can select single trees from the Graphical User Interface (GUI) and, for each wave-sample, a sphere with radius proportional to its amplitude is created and visualised [18].

Link: <<http://fullanalyze.sourceforge.net/>>

- **SPDlib**: exports discrete LiDAR and visualises either the samples that are above a threshold level as points or the extracted discrete point cloud. It also colours them according to their intensity value [19].

Link: <<http://www.spdlib.org/>>

Echo decomposition and extraction of peak points identifies significant features and further enables the interpretation of the data within existing workflows and software that support discrete LiDAR data. For example, the discrete LiDAR can be analysed using:

- **Lag**: a visualisation tool for analysing and inspecting discrete LiDAR point clouds.

Link: <<http://arsf.github.io/lag/>>

- **Quick Terrain Modeller** : a 3D discrete LiDAR points visualiser, that can generate Digital Elevation Models (DEM) and Digital Terrain Models (DTM).

Link: <<http://appliedimagergy.com/>>

- **LASTools** : a tool set that classifies noise, visualises point clouds, clips data.

Link <<https://rapidlasso.com/lastools/>>

The DASOS approach to interpreting FW LiDAR data is fundamentally different from the aforementioned software packages. On the one hand, converting FW LiDAR into discrete peaks eases their usage, since existing workflows support discrete LiDAR. On the other hand, FW LiDAR contains information about pulse width that is not

preserved after peak point extraction. Also the comparison of point clouds depends on the density of the emitted pulses; problems arise with the sinusoidal scanning pattern of, for example, the Leica system, resulting in higher numbers of samples at the edges of the swath and lower in the middle. For these reasons, in DASOS, this information is accumulated from multiple shots into a voxel array, building up a 3D density volume. The correlation between multiple pulses in a voxel representation produces a more accurate and complete representation, which confers greater noise resistance and it further opens up possibilities of vertical interpretation of the data. The idea of voxelising FW LiDAR data is explained in the following section 4.2.

4.2 Voxelisation for Interpreting FW LiDAR data

Voxelisation of FW LiDAR data was first introduced by Persson et al., who used it to visualise waveforms using different transparencies [20] and [it has been adopted as the future of FW LiDAR data with the literature moving toward that direction](#). In 2016-17, Cao et al used it for tree species identification [21], Hancock et al improved canopy height models of vegetation [22] and Sunmall et al characterised forest canopy from a voxelised vertical profile [9]. [The innovative approach of voxelising the FW LiDAR data](#) is an integral part of this thesis and it is used for both visualisations and classifications [23] [24].

The FW LiDAR data are voxelised by inserting the wave samples into a 3D regular grid and constructing a 3D discrete density volume. According to Persson et al, each wave sample is associated with the 3D cell, named voxel, that it lies inside. If multiple samples lie inside a voxel then the sample with the highest intensity is chosen [20]. In order to reduce noise, there are two differences between this approach and the way FW LiDAR data are voxelised in DASOS.

At first a threshold is used to remove low level noise, because when the length of a recorded waveform is longer than the distance between the first hit point and the ground, the system captures low signals for the remaining sampling time period after the pulse has been absorbed by the ground, which results pure noise. For that reason, the samples whose intensity is lower than a user-defined noise level/threshold are discarded.

As before, each wave sample is associated with the voxel that it lies inside. [The second difference is how DASOS overcomes the uneven number of samples per voxels, which is primarily caused by the differing angle at which the LiDAR shot passes through voxels directly below the sensor and those off to the sides.](#) The intensity of each sample is the laser intensity returned during the corresponding time interval. For example, if 5 samples are inside a voxel and the waveform is digitised at 2ns, then the laser

intensity associated with that voxel corresponds to a 10ns waveform sampling length. For comparison purposes, it's essential to keep the waveform length consistent across the voxels. To overcome this issue in DASOS, the average intensity of the samples that lie inside each voxel is taken, instead of choosing the one with the highest intensity [20]. This way, the likelihood that the 3D volume will be affected by outliers and high noise is reduced. The following equation shows how the intensity value of a voxel is calculated:

$$I_v = \frac{\sum_{i=1}^n I_i}{n} \quad (4.1)$$

where I_v is the accumulated intensity of voxel v , n is number of samples associated with that voxel and I_i is the intensity of the sample i .

To sum up, during voxelisation, the area of interest is divided into voxels. The samples of the FW LiDAR data are inserted inside this 3D discrete density volume and normalised such that equally sized waveform length is saved inside each voxel. The result is a 3D discrete density volume of the scanned area. Figure 4-1 depicts this process in 2D.

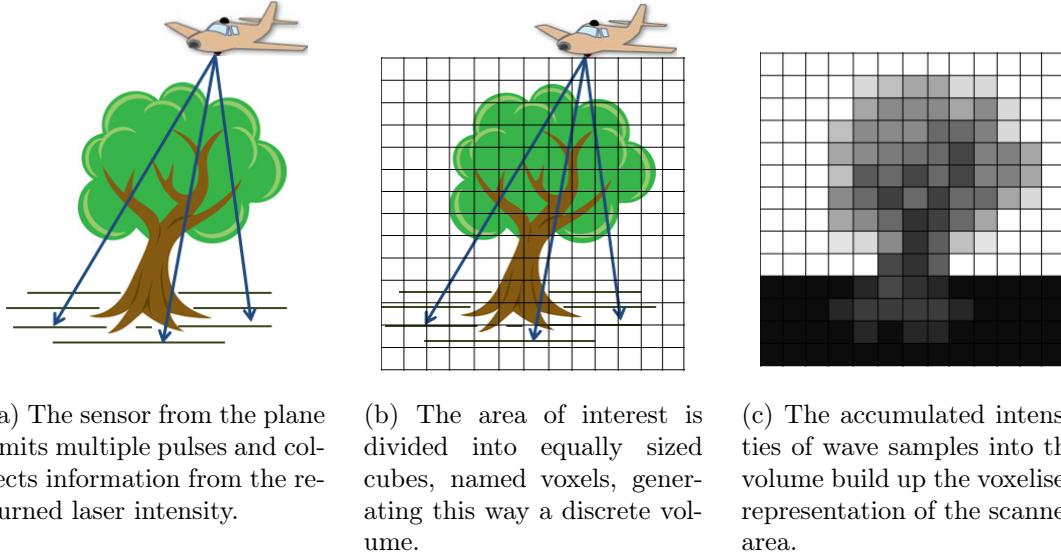


Figure 4-1: The above images depict the voxelisation process of the FW LiDAR data in 2D. Please note that the voxelisation output in Figure 4-1c shows how ideally the result would look. But in reality, a number of trees may be disconnected from the ground due to missing information about their trunk.¹

¹The tree and plane images are taken from: <http://images.clipartpanda.com/tree-clip-artKij4jKriq.jpeg> & http://gmv.cast.uark.edu/wpcontent/uploads/2013/01/ALS_scematic.jpg

4.3 The functionalities of DASOS

So far, an overview of existing software packages supporting FW LiDAR was given (Section 4.1) and it was explained how DASOS differs from them by voxelising the waveforms (Section 4.2). In this section, the three main functionalities of DASOS are described in Tables 4.1, 4.2 and 4.3.

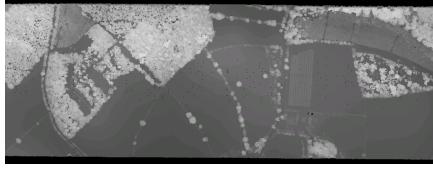
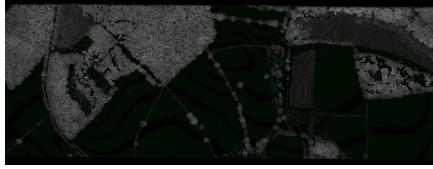
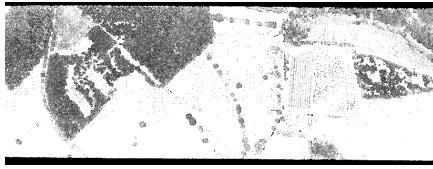
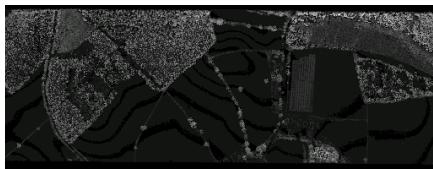
Each functionality is linked to a number of thesis sections, which describe the algorithms implemented and related applications. In a few words, the 3D visualisations are useful in forestry for reducing fieldwork and improving planning of field trips (e.g. checking whether a road passes through a fieldplot area). The 2D metrics allow simultaneous interpretation of FW LiDAR data and hyperspectral imagery. They could also be used in GIS software. In this thesis, they are used for generating tree coverage maps. Last but not least the priors enable 3D feature detection and they are used for detecting dead standing trees.

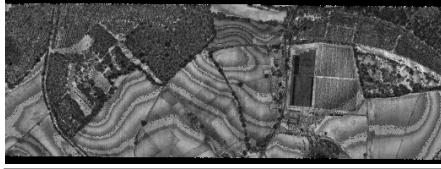
First Functionality: 3D Polygon Mesh Generation			
Input	Description	Output Example	Output Format
LAS1.3	3D Polygon Mesh Constructed from the volumetric representation (algorithms and user-defined parameters are explained in Section 5 while optimisation approaches are discussed in Section 6)		.obj
LAS1.3 and level 1 (.bil & .igm)	3D Coloured Polygon Mesh Projecting 3 user-defined hyperspectral bands on the mesh (Section 7)		.obj & .png

Table 4.1: The 1st functionality of DASOS that generates 3D polygonal meshes.

**Second Functionality: Generation of 2D metrics
aligned with hyperspectral imagery**

In Section 7 a selection of the following metrics are used
for generating tree coverage maps

Input	Metric Description (L for LiDAR metrics & H for hyperspectral metrics)	Output Example	Output Format
LAS1.3	L0 - Height: The distance between the top non-empty voxel and the lower boundaries of the volume.		.asc
LAS1.3	L1 - Thickness: The distance between the first and last non empty voxels in every column of the 3D volume.		.asc
LAS1.3	L2 - Density: Number of non-empty voxel over all voxels within the range from the first to last non-empty voxels.		.asc
LAS1.3	L3 - First Patch: The number of non-empty adjacent voxels, starting from the top non-empty voxel in that column.		.asc
LAS1.3	L4: Last Patch: The number of non-empty adjacent voxels, starting from the lower non-empty voxel in that column.		.asc

LAS1.3	L5 - Edge detection: The average height difference of neighbouring pixels.		.asc
LAS1.3	L6: Lowest Return The height of the lowest non empty voxel (the actual heights are very low and close to each but the example image has been scaled and the different seems bigger)		.asc
LAS1.3	L7: Maximum Intensity The maximum intensity of each column		.asc
LAS1.3	L8: Average Intensity The average intensity per column		.asc
LAS1.3 and level 1 (.bil & .igm)	H0 : Mean The mean of the hyperspectral spectrum.		.asc
LAS1.3 and level 1 (.bil & .igm)	H1: Standard Deviation ¹ The standard deviation of the hyperspectral spectrum at each pixel.		.asc

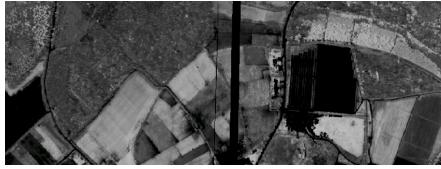
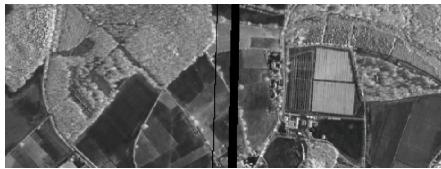
LAS1.3 and level 1 (.bil & .igm)	H2: NDVI The Normalised Difference Vegetation Index indicates whether green vegetation exists or not and it is derived from the electromagnetic spectrum as follow: $NDVI = \frac{NIR - VIS}{NIR + VIS} \quad (4.2)$ <p>where the NIR is the near-infrared region of the spectrum (700-2500nm) and VIS is the Visible/Visual spectrum (430-770) [25].</p>		.asc
LAS1.3 and level 1 (.bil & .igm)	H3: Spectral Signature ¹ The squared spectral difference between each pixels' spectrum and the generalised vegetation signature retrieved from USGS Digital Spectral Library [26].		.asc
LAS1.3 and level 1 (.bil & .igm)	H4: Band A single user defined hyperspectral band.	 	.asc .asc

Table 4.2: The 2nd functionality of DASOS that generates 2D metrics in ASCII format.

Third Functionality: 3D Priors / Signatures			
The 3D priors/signatures characterise objects or local areas in 3D.			
Input	Description	Output Example	Output Format
LAS1.3	3D Priors with raw intensities	Please Look at Figure 4-2	.csv
LAS1.3	3D Priors with processed intensities	Please Look at Figure 4-3	.csv

Table 4.3: The three functionalities of DASOS

Index	centroid_x	centroid_y	V0_0_0	V0_0_1	V0_0_2	V0_0_3	V0_0_4	V0_1_0	V0_1_1	V0_1_2	V0_1_3	...
0	251836.109	6048994.5	7	14	10	26	0	0	9	10.25	11.875	...
1	251843.906	6048980.5	0	0	0	0	0	0	0	0	0	...
2	251846.312	6048979	9	60.75	70.75	13	8	0	0	0	7.667	...
3	251849.312	6049022.5	48.556	93.222	20.5	0	7	0	0	0	0	...
4	251851.703	6048988	100.2	53.222	10.5	7.143	0	0	0	0	47.25	...
5	251852.906	6048975	0	0	0	0	0	26.875	0	10.444	13.182	...
6	251857.109	6048974	0	0	0	0	0	45.667	93	16.333	7.25	...
7	251858.312	6049010.5	0	0	0	0	0	0	0	8	6	...
8	251860.703	6048984	0	45.75	8	7.333	0	0	0	0	6.8	...
9	251861.312	6049000	0	0	0	0	0	0	0	0	0	...

Figure 4-2: Example of .csv files with priors exported. These priors contain the raw intensities of the voxels.

Index	centroid_x	centroid_y	Height_Middle_Column	Height_Mean	Height_Median	Height_Std	Sum_Int	Diff_X	...
0	251836.109	6048994.5	36	35.5	36	0.943	95.125	...	
1	251843.906	6048980.5	19.8	20.1	20.4	0.671	0	...	
2	251846.312	6048979	16.8	16	15.6	1.02	169.167	...	
3	251849.312	6049022.5	36	35.7	36.6	0.964	169.278	...	
4	251851.703	6048988	17.4	16.2	16.2	0.346	408.065	...	
5	251852.906	6048975	27	26.4	26.4	0.917	68.537	...	
6	251857.109	6048974	17.4	17.4	18	0.849	162.25	...	
7	251858.312	6049010.5	40.8	40	39.6	1.02	251.36	...	
8	251860.703	6048984	17.4	16.6	16.2	0.663	67.883	...	
9	251861.312	6049000	19.8	20.1	20.4	0.671	0	...	

Figure 4-3: Example of .csv files with priors exported. These priors contains proccesed information about the the local area of interest (i.e. spread of non empty voxels).

¹The marked metrics of Table 4.2 were implemented specifically for the tree coverage maps [24] and they are not available on the released version of DASOS.

It is further worth stating that detailed information about DASOS is provided at: <<http://miltomiltiadou.blogspot.co.uk/2015/03/lat13vis.html>>. This link also indicates how to download DASOS, the complete user-guide and the source code, as well as where to seek support while using it.

4.4 Summary and Discussion

Along with supporting the research in this thesis, the open source software DASOS was developed to encourage foresters to use FW LiDAR data. The main way of interpreting FW LiDAR data in DASOS is fundamentally different from the state-of-art available software packages. In a few words, the FW LiDAR data are voxelised by inserting the wave samples into a 3D discrete density volume, which preserves an extra parameter (the echo width) in comparison to point extraction algorithms. It also accumulates intensity values from multiple shots and stores them into a 3D regular grid, resolving this way the problem with the sinusoidal footprint / uneven scanning pattern of the Leica system.

There are three main functionalities of DASOS: the construction of 3D polygon meshes, the generation of 2D metrics aligned with hyperspectral images and characterisation of objects using 3D priors/signatures. The visualisation outputs are also state-of-art since previous visualisations talk about points [19] or spheres [18], while DASOS is able to create closed polygon representation. In addition, the integration of various sensors allows simultaneous interpretation of their data and, in section 7, it is shown that this confers better results for generating tree coverage maps. The 3D priors allow local inspection of data and they are used in section 8 for dead standing tree detection in native Australian forests.

Finally, it worth mentioning that there a few individuals/organisation that showed interest in using DASOS and, in the future, usage of it, its derivatives or the concepts employed in it are expected to increase in remote forest surveys (i.e. for commercial forest stocking estimation or for infected trees detection and treatment).

Chapter 5

Surface Reconstruction from Voxelised FW LiDAR Data

5.1 Introduction

To briefly summarise the previous sections, FW LiDAR data (Section 2) are laser scanning data particularly useful in Forestry, but the huge amount of information recorded make handling of the data difficult. The open source software DASOS (Section 4.3) was developed along with this thesis to ease the usage of the data. DASOS voxelises (Section 4.2) the data before interpretation and this approach is fundamentally different from the related, state-of-art software packages. The output of the voxelisation is a 3D discrete density volume.

In order to visualise a voxel volume, it must be rendered in some form. This chapter explains the process of reconstructing the surface of the scanned area from the 3D voxelised FW LiDAR. At first, volumetric rendering¹ approaches are briefly explained in Section 5.2. Section 5.3 gives a mathematical definition to the voxelised data, while Section 5.4 describes the actual algorithm used to extract a surface. Finally, the results are given in Section 5.5.

5.2 Rendering Approaches of Volumetric Data

Even though the concept of visualising 3D discrete density volumes (Volumetric Visualisations) is new in forestry and remote sensing, it has been widely researched in medical imaging and visual effects. There are two approaches to visualising volumetric data.

¹Volumetric rendering refers the process of visualising 3D Volumes.

The first approach is direct rendering, which repeatedly generates 2D images according to the view point (the camera). It is like "taking photos" *** Neill: Not sure about the analogy? Can you include a diagram from a paper or textbook to show what you mean? from a camera and putting them in a sequence to produce an interactive video. An example of direct rendering approach is ray-tracing. Ray-tracing generates images by "taking photos"; rays are cast from the view point, passing through each pixel on a screen and carrying on into the volume. Intensity values are assigned to the pixels according to the nearest intersections [27]. Ray-tracing can be time expensive depending on the complexity of the scene and, for that reason, some of the literature focuses on parallelising the ray-casting process. By introducing parallelisation, real time rendering of small volumetric data (256^3) was achieved by Pfister et al. in 1999 [28]. Also, after the release of the CUDA hardware [29] (which is a parallel computing platform on recent nvidia graphics cards), Crassin et al. achieved real-time rendering of billions of voxels in 2009 [30].

The second approach is rasterisation, which is a method that maps primitive polygons (typically triangles) to pixels. It is widely used in computer games, supported directly by common hardware acceleration systems and it is significantly faster than ray-tracing. Furthermore, interactive operations (e.g. measuring the distance between two trees) are trivial calculations on primitives/polygonal meshes and they are easy to implement. In order to use this approach with volumes, they must be first converted to primitives. This is commonly accomplished by surface reconstruction, referring to the extraction of a polygonal mesh, which is a set of primitives like triangles, from the volumetric data. Constructing a surface may take several minutes, but real time visualisations of polygonal meshes are supported by free animation packages (like Blender and Meshlab), in addition to being easy to implement. So, even though it is possible to implement real-time interactive environments using direct rendering of the big voxel data, volumetric visualisation of FW LiDAR data is a new concept in remote sensing and, for simplicity, this thesis uses surface reconstruction.

5.3 Algebraic Definition of the Volume

In computer graphics, objects can be defined using a function rather than being constructed from primitives. Those objects are called either implicit or algebraic. Implicit representation of objects enables a mathematical definition of the 3D discrete density volume generated from the FW LiDAR data (Section 4.2).

Algebraic objects were firstly introduced in computer graphics by Blinn in 1982 [31] to enable the definition of complex objects without saving a large amount of primitives;

in some cases, primitives cannot accurately represent a shape (e.g. a sphere cannot be represented fully by a triangle mesh). Each object is defined by a function $f(X)$ and the iso-surface value α . The iso-surface value (iso-level) defines the boundaries of the object; for an object $[f(x), a]$ every n-dimensional point X that lies on the surface of the object satisfies the condition $f(X) = \alpha$. To be more accurate, the following rules apply according to Pasko et al. [32]:

- $f(X) = \alpha$, when X lies on the surface of the algebraic object
- $f(X) > \alpha$, when X lies inside the algebraic object and
- $f(X) < \alpha$, when X lies outside the algebraic object

Regarding the algebraic representation of the 3D voxelised FW LiDAR data, X is a three dimensional point (x, y, z) representing the longitude, latitude and height respectively and $f(X)$ is a function that takes X as input and returns the accumulated intensity value of the voxel that X lies inside. Also, the iso-surface value α is a user defined parameter. Even though it is closely related to the noise threshold used for filtering during voxelisation (Section 4.2), it is different. The noise threshold filters low intensity samples before the volume is constructed, while the iso-surface value defines the boundaries of the object and it can be modified after the voxelisation because it doesn't affect the intensity values of the 3D voxelised FW LiDAR. Figure 5-5 demonstrates how the iso-level parameter affects the output of the surface reconstruction of the voxelised FW LiDAR data in comparison to the noise filtering.

****NEIL:** for the purple part: We need to be careful here - on I explained a while ago, the numbers you are putting in the voxels are appropriate since you average.

5.4 Surface Reconstruction with the Marching Cubes Algorithm

Even though algebraic representation is beneficial in reducing storage memory, visualising implicit objects is not straight forward, since they contain no discrete values. As described above in rendering volumes, this problem can be addressed either by direct rendering or surface reconstruction (Section 5.2).

The Marching Cubes algorithm is an algorithm that extracts an iso-surface from the implicit volumetric field as a polygonal mesh using a look up table. Let's assume that $f(X)$ defines an implicit object. At first the space is divided into cubes. Each cube is defined by eight corner points and each corner point lies either inside or outside the iso-surface. By enumerating all the possible cases and linearly interpolating the

intersections along the edges, the surface of the implicit iso-surface is constructed [33]. The output is a polygonal mesh, a number of adjacent triangles constructed according to the user-defined iso-surface value α of the implicit object.

for the next paragraph (again, perhaps a diagram)

The normals² are calculated afterwards. According to Lorensen and Cline [33], the normal of each vertex is calculated by measuring the local gradient change. Even though this work well on smooth object (e.g. a sphere defined by its equation), because of the high gradient changes in the voxelised FW LiDAR data this algorithm results into normals pointing into inconsistent directions. This is a problem because when the normals are not consistent, the surface of the object appears rough. For that reason, in DASOS the normal of each vertex is derived by the average normal of its adjacent triangles.

Additionally it is worth highlighting that the sampling of the Marching cubes is independent from the sampling of the 3D density volume. But consistency between the two is required to avoid artefacts. Let's assume the discrete volume has $(n \times m \times k)$ voxels, then the suggested sampling of Marching Cubes is $((n+1) \times (m+1) \times (k+1))$, as shown on Figure 5-1; the black grid represents a 2D density grid and the blue grid represents the suggested sampling of the polygonisation. Please note that every point that lies outside the volume is considered to be outside the implicit object. Figure 5-1b shows the effects of oversampling on a low resolution 3D density volume. On the right image the sampling of the volume appears as linear lines and squares on the forested areas because of the Marching Cubes' oversampling. Even though the right polygonal mesh looks blurred, it has been correctly sampled and the blur is because of the low resolution of the volume. Nevertheless there are no geometrical shapes on forested areas and once the resolution is increased then blur will disappear.

5.5 Results

The output of DASOS is a polygonal mesh exported into a .obj file, which is a standard graphics format. The .obj files can be loaded into various animation software tools like Maya and Meshlab (Figure 5-2). Figure 5-3 shows polygonal meshes generated using NERC-ARF data from three different areas in the UK. The region of interest is also user defined. The user defines whether an entire flightline or selected area is polygonised (Figure 5-4).

²A normal is a vector that is perpendicular to the surface of a polygonal mesh. In graphics, the normals are important for calculating light illumination and each vertex is associated with one for smooth rendering of surfaces.

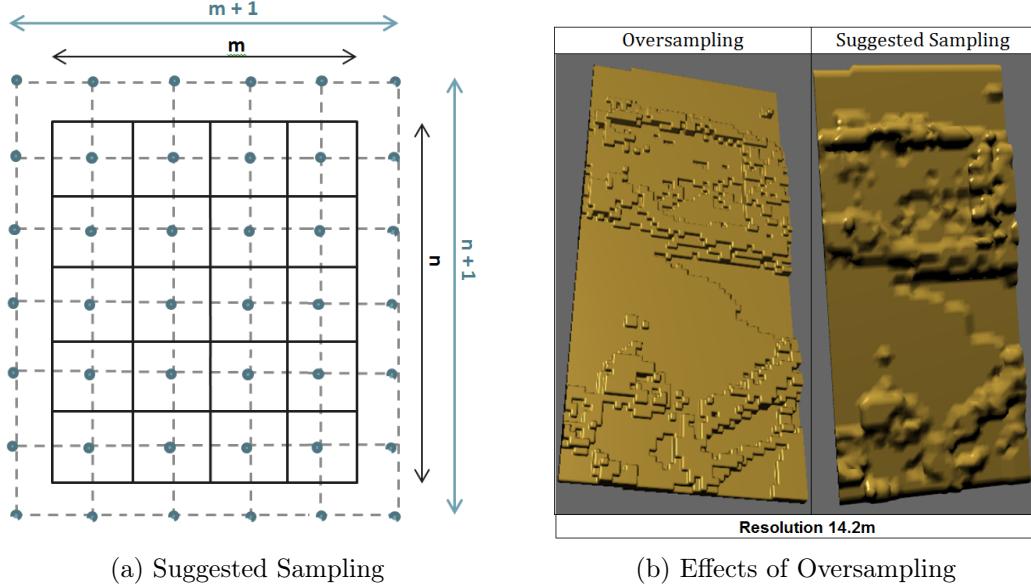


Figure 5-1: The suggested sampling during polygonisation using the Marching Cubes Algorithm

Furthermore, there are three main user-defined parameters and Figure 5-5 shows how the results are affected once modified:

1. The voxel length controls the resolution of the output; the bigger the voxel length is the lower the resolution and the number of cubes are.
2. The iso-level is the boundary that defines whether a voxel is inside or outside the implicit object. When the iso-level is increased, the number of voxels that are considered inside the implicit object decreases. For that reason, when it is too high most of the voxels are outside the boundary and the object seems to disappear.
3. The noise level is the threshold of the low level filtering applied during voxelisation (Section 4.2). If the noise level is too low, then the noise covers significant features of the data and when it is too high important information are discarded and the object seems to disappear again.

Aside from computer-based visualisation, it is even possible to 3D print the meshes using something like MakerBot. There are some difficulties as the meshes are not manifold³ (figure 5-6). Simplification of the mesh would have eased the processing of the .obj file in MakerBot.

³A non-manifold polygonal object may have triangle below the outside surface of the object

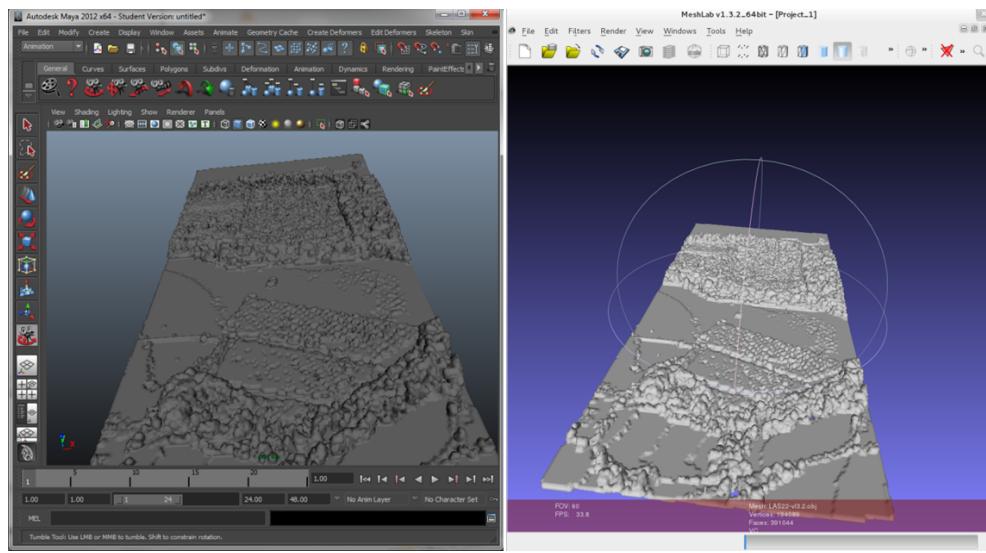


Figure 5-2: Visualising the output of DASOS into animation software packages (Maya and Meshlab)

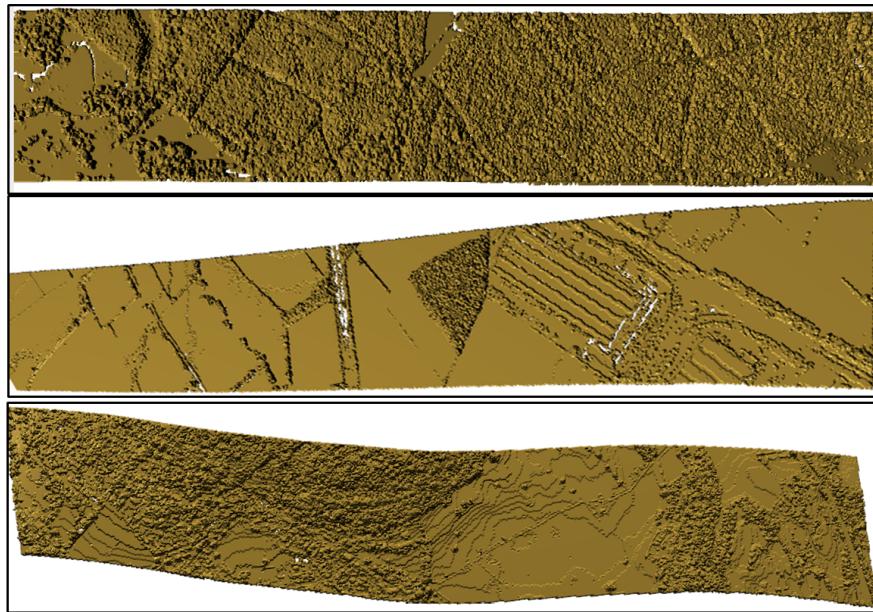


Figure 5-3: Polygonising NERC-ARF FW LiDAR data captured at different areas (New Forest, Milton Keynes and Eaves Wood)

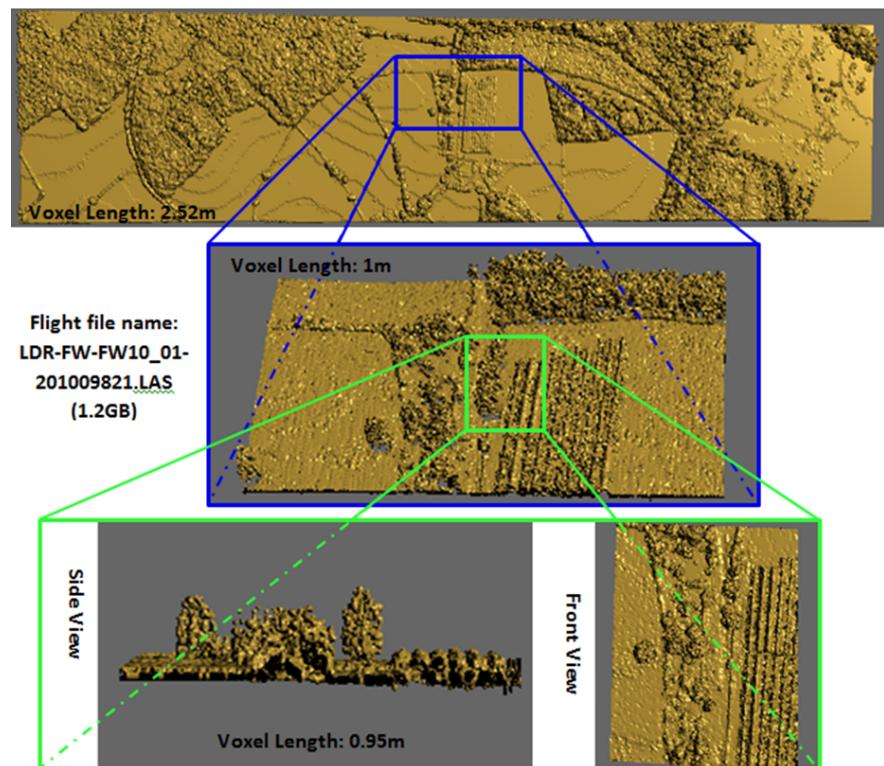


Figure 5-4: Selecting Region of Interest

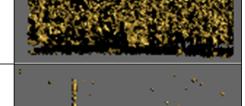
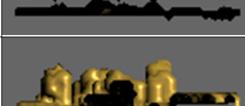
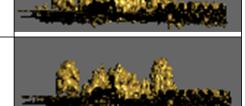
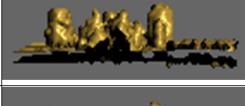
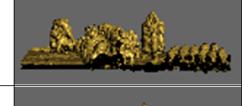
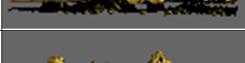
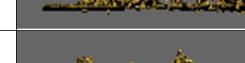
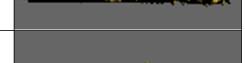
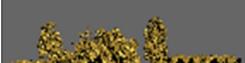
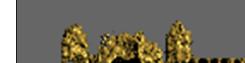
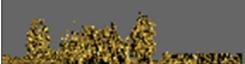
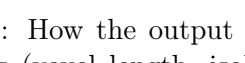
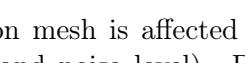
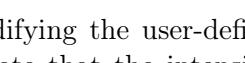
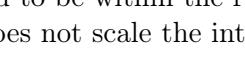
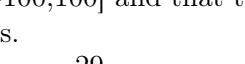
Voxel Length	Visualisation with different voxel lengths	Iso-level *	Visualisations with various isolevels	Noise Level	Visualisations with various noise levels
16.67 m		60		0	
10.0m		45		5	
7.14m		30		10	
5.7m		15		15	
4.44m		0		17	
3.33m		-15		20	
2.5m		-30		25	
2.0m		-45		30	
1.43m		-60		40	
1.2m		-75		60	
1.0m		-85		75	
0.8m		-95		100	
0.67m		-100		135	

Figure 5-5: How the output polygon mesh is affected by modifying the user-defined parameters (voxel length, isolevel⁴ and noise level). Please note that the intensities were scaled to be within the range [-100,100] and that the currently released version of DASOS does not scale the intensities.

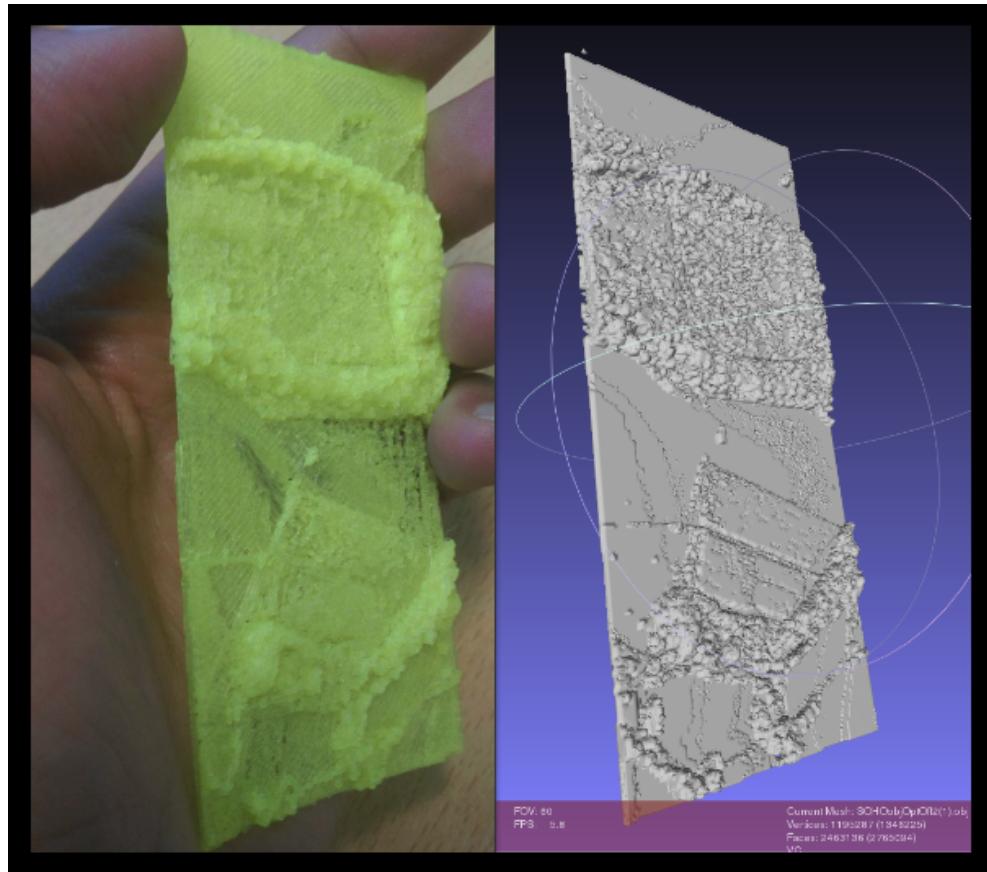


Figure 5-6: 3D printing of New Forest FW LiDAR data

Chapter 6

Optimisation Attempts for the Surface Reconstruction

Chapter 7

Alignment with Hyperspectral Imagery

7.1 Introduction

In this chapter, the hyperspectral images are introduced to improve the visual output of the polygonal meshes derived from the FW LiDAR data (Chapter 5). The combination of NERC-ARF LiDAR and hyperspectral data from New Forest (Figure 2-1) for generating tree coverage maps is investigated.

Please note that definitions (i.e. bands and level-1) are used in this chapter and if you are not familiar with these terms it is highly recommended to read again Section 2.4, which explains everything about hyperspectral imagery.

7.2 Previous Work

Regarding the integration of FW LiDAR and hyperspectral data in remote forest surveying, there are diverse opinions on whether the integration of multi-sensor data improves remote forest surveying. Clark et al. attempted to estimate forest biomass but no better results were observed after the integration [34], while the outcomes of Anderson et al. for observing tree species abundances structures were improved after the integration of the data [35].

Buddenbaum et al. [36], and Heinzel and Koch [37], used a combination of multi-sensor data for tree classifications. Buddenbaum et al. use fusion of data to generate RGB images from a combination of FW LiDAR and hyperspectral features, although the fusion reduces the dimensionality of a classifier [36]. In that study, three different classifiers were implemented and the Support Vector Machines (SVMs) returned the

best results. SVMs were also used in [37] to handle the high dimensionality of the metrics (464 metrics). In that research a combination of FW LiDAR, discrete LiDAR, hyperspectral and colour infrared (CIR) images are used. Each of the 125 hyperspectral bands was directly used as a feature in the classifier, contributing to the high dimensionality.

7.3 Spatial Representation of Hyperspectral Pixels for Quick Search

For the New Forest Dataset (Figure 2-1), there are both FW LiDAR and hyperspectral data. The data are collected from two independent instruments and, while they are flown together, each instrument has a slightly different view point, a different resolution/sensing mechanism and data collection parameters (e.g. integration time). Therefore the data collected are not aligned to each other (e.g. for each waveform there is no trivial-correspondence to a spectral measurement). To integrate the data geo-spatially, alignment of the data is required. As mentioned at Section 2.4, in order to preserve the highest possible quality and reduce blurring that occurs during geo-rectification, data in the original sensing geometry (level-1) are used.

In Anderson et al. [35], an inverse distance weighted algorithm is used to rasterise the hyperspectral images and the pixel size is constant, 15.8m, while in this study an approach similar to Warren et al. [13] is used and the resolution is changeable. The main concept of our geo-rectification algorithm is to be able to find the nearest hyperspectral pixel to a point in the fastest possible way. For that reason, a spatial representation of the hyperspectral pixels is created by importing the pixels into a 2D grid, similar to [13]. The cell size of the grid in meters is constant, but the dimensions of the grid in number of squares (n_x, n_y) can be varied according to the chosen average number of pixels per square (A_{ps}):

$$n_x = \sqrt{\frac{n_s^2}{A_{ps}}} \quad n_y = \sqrt{\frac{n_l^2}{A_{ps}}} \quad (7.1)$$

Where n_s is the number of samples and n_l is the number of lines of the hyperspectral cube (figure 2-4).

Furthermore, Warren et al. [13] uses a tree-like structure, here a structure similar to hash tables is used to spatially represent the pixels and speeding up searching. As shown in Figure 7-1, for each cell there is a bucket containing all the points that lie inside it. The hash function takes as input the unique key of the cell and returns the

memory location of the corresponding bucket. The key of a cell with coordinates (x_s, y_s) is equal to $(x_s + y_s * n_x)$ where n_x is the number of pixels in the x-axis.

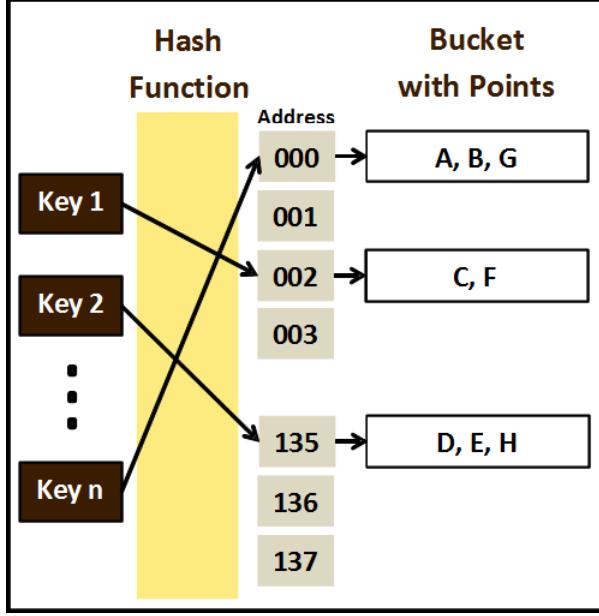


Figure 7-1: The hash table of the spatial representation of the hyperspectral pixels; each bucket contains all the pixels in a square and has a unique key derived from the coordinates of its square. The hash function takes as input the key and returns the address in memory of the corresponding bucket.

The next step is for a point (x_v, y_v, z_v) to find the pixel whose geolocation is the closest to it. First we project the point into 2D by dropping the z coordinate and then we find the square (x_s, y_s) that the projected point $\mathbf{v}(x_v, y_v)$ lies inside, as follow:

$$x_s = \frac{x_v - X_{min}}{X_{max} - X_{min}} * n_x \quad (7.2)$$

$$y_s = \frac{y_v - Y_{min}}{Y_{max} - Y_{min}} * n_y \quad (7.3)$$

Where X_{max} , X_{min} , Y_{max} , Y_{min} are the geospatial boundaries of all the hyperspectral image and n_x, n_y are the number of pixels in the x and y axis accordingly.

From the square (x_s, y_s) we can get the set of pixels that lie inside the same square with the point of our interest. Let's assume that the geospatial locations of these pixels are the vectors $\mathbf{g}_1, \mathbf{g}_2, \mathbf{g}_3, \dots, \mathbf{g}_n$ respectively. Then, by looping through that set of pixels, we can find the pixel i that is most likely to be the closest pixel to the point

$\mathbf{v}(x_v, y_v)$:

$$i = \arg \min |\mathbf{v} - \mathbf{g}_i|^2. \quad (7.4)$$

Finally, there is the case of the closest point to be within an adjacent square and this occurs when the point is very close to the edges of the square. Even though this was not implemented in DASOS when the paper [24] was published, it can be done by checking the distance between the edges of the square and the point. If this distance is smaller than the distance between pixel i then we can loop through the points of the corresponding adjacent square and check whether there is another pixel closer to point \mathbf{v} than pixel i . Similarly, by checking the distance between the point \mathbf{v} and the corners of the square (x_s, y_s) , the case of the closest point to exist inside a diagonally-adjacent square is also covered.

7.4 Projecting hyperspectral images into polygon meshes generated using FW LiDAR data

This section focuses on projecting the (level-1) hyperspectral images onto the polygonal meshes reconstructed from the FW LiDAR data as explained in Section 5.4. As shown in Figure 7-2, the result is a coloured polygon mesh. That mesh is saved into two files:

- the .obj file that contains the 3D geometry and
- the .png file that contains the 2D texture image

The (level-1) hyperspectral images look deformed because the pixel size is not consistent. ([Figure 7-2 shows that inconsistency](#)). DASOS resolves this problem by adjusting the texture coordinates of the polygonal mesh according to the geolocation of the pixels. The texture coordinates (u, v) of each vertex lies inside the range $[0, 1]$ and if they are multiplied by the height/width of the texture, then the position of the corresponding pixel of the texture is given. In order to calculate the texture coordinates of each vertex (x_v, y_v, z_v) , the spatial representation of the hyperspectral pixels (explained at Section 7.3) is used for quickly detecting the pixel (x_p, y_p) , whose geolocation is the closest to a vertex. By dividing the pixel position with the number of samples (n_s) and lines (n_l) in the hyperspectral image, the texture coordinates (u, v) of each vertex $v(x_v, y_v)$ are calculated:

$$u = \frac{x_p}{n_s} \quad v = \frac{y_p}{n_l} \quad (7.5)$$

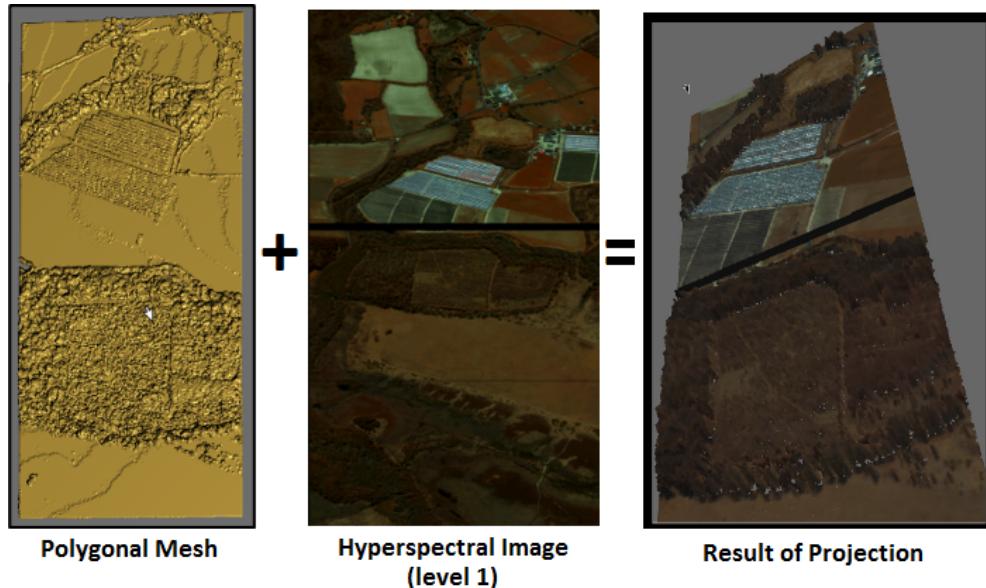


Figure 7-2: Projecting hyperspectral images into the polygonal meshes

Regarding the outputs, the texture coordinates of the polygonal mesh are added into the .obj file, while the 2D texture is simply an image generated from three user-selected bands for the RGB colours. The width of the image is equal to the number of hyperspectral samples per line while its height is equal to the number of lines.

7.4.1 Results

The results of the projection are coloured polygonal meshes. Each coloured polygonal mesh is exported into two files:

1. the .obj file contains the 3D geometry with all the information about the vertices, edges, faces, normals and texture coordinates, and
2. the .png is the 2D texture (an RGB image) and it is aligned with the texture coordinates of the polygonal mesh.

Figure 7-3 shows how the visual output is affected by projecting hyperspectral data from different sensors and by changing the selected bands.

Bands	150th, 60th, 23rd	137th, 75th, 38th	Bands	137th, 75th, 38th	23rd, 120th, 201st
EAGLE INSTRUMENT (Visible and Near Infra-red)			HAWK INSTRUMENT (Short Wave Infra-red)		

Figure 7-3: Results of Alignment; the left table shows the results of projecting hyperspectral images from the Eagle instrument onto the polygonal meshes generated using FW LiDAR data and the right hand side table shows results using the Hawk instrument.

7.5 Tree Coverage Maps

As mentioned before, there are diverse opinions on whether or not integration of remotely sensed data improves forest monitoring [34] [35]. For that reason, a simple pixelwise classifier was implemented to test how the integration of NERC-ARF data, using metrics generated from DASOS, performs for generating tree coverage maps.

The metrics generated from both hyperspectral and FW LiDAR data are 2D aligned images (Table 4.3). In other words, the pixel (x, y) has the same geospatial coordinates in every metric. Further the resolution of the metrics depends on the resolution of the 3D voxelised FW LiDAR data (Section 4.2). If the dimensions of the volume are (x, y, z) then the dimensions of the metrics are (x, y) . For the LiDAR metrics, each pixel is coloured according to the information derived from the corresponding column. Regarding the hyperspectral metrics, (level-1) data are used to preserve the highest possible quality. The method in Section 7.3 was used for finding the pixel from the hyperspectral data with the closest geospatial location to the centre of each column of the 3D voxelised FW LiDAR.

The metrics used for generating tree coverage maps are grouped into two categories (FW LiDAR and hyperspectral metrics):

- FW LiDAR: Height (L0), Thickness (L1), Density (L2) and First Patch (L3)
- Hyperspectral: Mean (H0), NDVI (H1), Standard Deviation (H2) and Spectral Signature (H3)

For more descriptive information and examples of the metrics please look at Table 4.3,

where all the functionalities of DASOS are listed.

7.5.1 Testing and Results

In this case, the total accuracy was increased with the integration of FW LiDAR data and hyperspectral images. A Naïve Bayesian classifier using a multi-variance Gaussian model is applied for distinguishing tree-covered areas from the ground. The main idea is for each pixel/column to find the class that is more likely to belong to Tree or Ground. Ground truth data were hand painted using 3D models generated with DASOS and were divided into training and testing data. There are three test cases and, for each test case, the following metrics are used:

- 1st test case uses the L0-L3 metrics that are generated from the FW LiDAR data.
- 2nd test case uses the H0-H3 metrics that are generated from the hyperspectral imagery.
- 3rd test case uses L0-L3 & H0-H3 which is a combination of metrics generated from either FW LiDAR data or hyperspectral imagery.

For each test case, an error matrix is generated to indicate the accuracy of the classification results as verified against the ground truth data (Tables 7.1, 7.2 and 7.3) [38]. Each row shows the number of pixels assigned to each class relative to their actual class. For example, the first row of Table 7.1 shows that 130445 pixels were classified as trees, where 125375 were actual trees and the rest 5070 were ground. From the error matrices, the classification accuracy of each test case was calculated and it is presented in Table 7.4.

Figure 7-4 depicts the coverage maps generated for each test case. Three areas are marked for comparison. In Area 1 there is low vegetation, in Area 2 there are short trees and in Area 3 warehouses. Area 1 was incorrectly classified when only the hyperspectral data were used; when the height information of the LiDAR data was included into the classifier, area 1 was correctly classified. Similarly, Area 2 was wrongly classified when using the only FW LiDAR metrics because the height of the trees was less than the average training samples. But since features from the hyperspectral data are not height dependant, the classification results of test case 1 (with hyperspectral metrics) was better at Area 2. Area 3 seems to confuse the first two classifiers in different ways, but the combination improved the results.

Finally, to demonstrate the usefulness of DASOS's polygonal meshes, the results of the tree coverage maps were projected into the polygon representations as shown in the following Figure 7-5.

		Ground truth data		
Results		Tree	Ground	Row Total
	Tree	125375	5070	130445
	Ground	45093	228495	273588
	Total	170468	233565	404033

Table 7.1: Error Matrix showing the pixel-wise classification results of the 1st test case that only uses hyperspectral data.

		Ground truth data		
Results		Tree	Ground	Row Total
	Tree	154768	39504	194272
	Ground	15700	194061	209761
	Total	170468	233565	404033

Table 7.2: Error Matrix showing the pixel-wise classification results of the 2nd test case that only uses FW LiDAR data.

		Ground truth data		
Results		Tree	Ground	Row Total
	Tree	152597	10548	163145
	Ground	17871	223017	240888
	Total	170468	233565	404033

Table 7.3: Error Matrix showing the pixel-wise classification results of the 3rd test case that uses both hyperspectral and FW LiDAR data.

	FW LiDAR	Hyperspectral Imagery	Both
Tree	73.55%	90.79%	89.52%
Ground	97.83%	83.09%	95.48%
Mean Average Precision	87.58%	86.34%	92.97%

Table 7.4: Classification accuracy of each test case

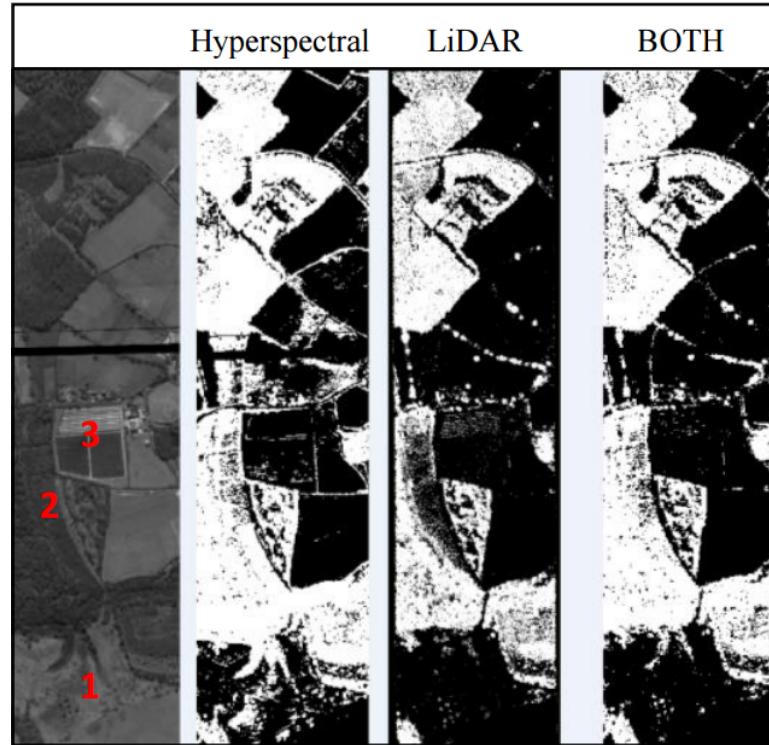


Figure 7-4: Visual Comparison of the results of the coverage maps

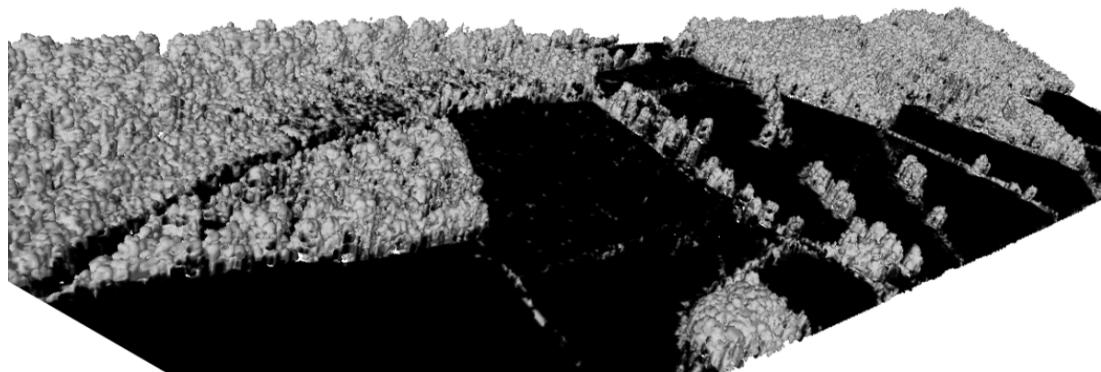


Figure 7-5: 3D Coverage model, generated by projecting the results of the tree coverage classification into a polygonal mesh.

7.6 Summary and Conclusions

In conclusion, this chapter describes an efficient way of aligning the FW LiDAR data and hyperspectral images using a spatial representation of hyperspectral pixels. The voxelisation of the FW LiDAR data also eases the generation of aligned metrics from both datasets. Furthermore, the resolution of the metrics is changeable and depends on the user-defined resolution of the voxelised FW LiDAR data. Additionally, since the closest pixel is always selected, regardless of the distance from the point of interest, the problem of having data at different resolution is automatically resolved.

Regarding the results, coloured polygonal meshes were generated using the alignment and the result demonstrated that the integration of this specific data has potential in remote forest surveying - aside from improving the visual appeal, it also improves automatic classification. This was shown using a simple classifier for generating tree coverage maps. The results were positive; the classification accuracy was improved by 5.39% when both datasets were used. A more sophisticated classifier would likely give even better results.

Chapter 8

Detection of Dead Standing Eucalyptus For Managing Biodiversity in Native Australian Forest

8.1 Introduction

8.1.1 The Importance of Dead Wood

The value of dead trees from a biodiversity management perspective is large. Once a tree dies, its contribution to our ecosystem continues. The woody structure remains for centuries and it contributes to forest regeneration while providing resources for numerous surrounding organisms [39]. As an indication, more than 4000 species inhabit dead wood in Finland [40], where an estimate of 1000 species has been extinct [41]. These species do not only include animals and birds but also organisms, like fungi. Fungi contributes to wood decaying, formation of hollows and biodiversity, which is an important factor for a resilient ecosystem [42]. Observing the changes of fungal diversity on decaying wood has an increased interest in science [43] [44] [45] in order to ensure the continuous existence of decaying wood in forests.

Specifically in Australia, tree hollows play a significant role in managing biodiversity. Nearly all arboreal mammals rely on hollows with the exception of the Koala and perhaps Ringtail Possums that preferentially make a stick nest, but they use hollows as well. Additionally, a large number of Australian bird species rely on hollows for shelters [46]. Nevertheless, Australia has no real hollow creators like the northern hemisphere

(e.g. Woodpeckers), and therefore it relies predominantly on natural processes of limb breakage, insect and fungal attack when access points are provided through damage caused by wind, storms and fire.

This kind of hollows take hundreds of years to form and because of that it is more likely to exist on dead trees. In Australia, studies predict shortage of hollows for colonisation in the near future [47] [48]. Therefore automated detection of them plays a significant role in protecting those animals. As an indicator of the importance of hollows in managing biodiversity, a list of a few of the species that rely on hollows was provided by the Forestry Corporation of NSW. Those species are shown at Figure 8-1. According to the Department of the Environment of Australian Government and the Government of Western Australia, six of them are protected, threatened or close to extinct [49] [50]. Figure 8-1 shows the species from the provided list and the six protected species have a red border and their names are bold in the description.

For the aforementioned reasons, monitoring dead trees is essential for having a resilient ecosystem. Nevertheless, the distribution of dead trees significantly varies making detection of them difficult [51]. Remote sensing approaches has been introduce to automate the process of monitoring forest and further increase the spatial resolution of the monitored area. The following section gives an overview of the related work undertaken in Remote Sensing.

8.1.2 Related Work

Remote Sensing was introduced for automatically detecting dead trees, because field-work is time consuming considering their variance spread and the size of the relevant forests. From a classification perceptive, the task of identifying dead standing and dead fallen trees is different. Fallen trees are identified by detecting segments or line-like features on the terrain surface using LiDAR data [52] [53]. Regarding standing dead trees, their shape (reduced number of leaves or broken branches) [54] and light reflectance (less green light illuminated) [55] are important factors for identifying them.

Previous work on dead standing trees detection performs single tree crown delineation before health assessment [54] [56]. Tree-crown delineation is usually done by detecting local maxima from the canopy height model (CHM) and then segmenting trees with watershed algorithm [57]. Improvements has been achieved by introducing markers controlled watershed [58] and structural elements of tree crowns with different sizes [59]. Additionally, Popescu and Zhao analyse the vertical distribution of the LiDAR points in conjunction with the local maximum filtering of CHM [60].

In the case of Eucalyptus, single tree detection is a challenge on its own, due to their irregular structure and multiple trunk splits. In other words, each tree trunks splits



Figure 8-1: A number of species that rely on tree hollows of which the red ones / bold ones are close to extinction: Kookaburra, Sulphur Crested Cockatoo, **Corella**, Crimson Rosella, Eastern Rosella, Galah, Rainbow Lorikeet, Musk Lorikeet, Little Lorikeet , Red-winged Parrot, **Superb Parrot**, Cockatiel, Australian Ringneck (Parrot), Red-rumped Parrot, Powerful Owl, Sooty Owl, Barking Owl, **Masked Owl**, **Barn Owl**, White-throated Treecreeper, Hollow Owl, **Brush-tailed Possum** (mammal) ¹

¹The images of the birds were taken from the following links (Retrieved on the 27th of April 2016): Kookaburra: <<http://tenrandomfacts.com/blue-winged-kookaburra/>>, Sulphur Crested Cockatoo: <<http://aussiegal17.deviantart.com/art/Sulphur-Crested-Cockatoo-08-153341893>>, Corella: <<http://www.theparrotplace.co.nz/all-about-parrots/long-billed-corella/>>, Superb Parrot: <<http://www.davidkphotography.com/?showimage=637>>, Crimson Rosella: <http://25.media.tumblr.com/tumblr_m3mo89c40r1r4t9h1o1_1280.jpg>, Eastern Rosella: <http://2.bp.blogspot.com/-pYxw51WjSOY/UB-LEFgd2KI/AAAAAAAAGw/9z60PUWE6TE/s1600/_GJS6601-as-Smart-Object-1.jpg>, Rainbow Lorikeet: <https://www.reddit.com/r/pics/comments/328fvc/a_rainbow_lorikeet_found_in_coastal_regions/>, Musk Lorikeet: <http://www.rymich.com/girraween/photos/animals/birds/medium/glossopsitta_concinna/glossopsitta_concinna_001.jpg>, Little Lorikeet: <<http://www.pbase.com/sjmurray/psittacidae>>, Red-winged Parrot: <<https://www.pinterest.com/pin/395894623469889727/>>, Cockatiel: <<http://up.parsipet.ir/uploads/Cockatiels-for-sale.jpg>>, Australian Ringneck (Parrot): <<http://ontheroadmagazine.com.au/wp-content/uploads/2015/09/Twenty-eight-parrot-2-min.jpg>>, Red-rumped Parrot: <<http://parrotfacts.net/wp-content/uploads/Red-Rumped-Parrot-on-a-tree.jpg>>, Powerful Owl: <http://farm1.staticflickr.com/219/495796536_f78dac04c1.jpg>, Sooty Owl: <http://www.mariewinn.com/marieblog/uploaded_images/screech2-738532.jpg>, Barking Owl: <<http://www.pcpimages.com/Nature-and-Wildlife/Birds/i-7JKSTp5/1/L/owl%20%281%20of%201%29-L.jpg>>, Masked Owl: <http://www.survival.org.au/images/birds/masked_owl_2_600.jpg>, Galah: <<https://www.pinterest.com/pin/537546905498955709/>>, White-throated Treecreeper: <<https://geoffpark.files.wordpress.com/2011/09/female-white-throated-treecreeper.jpg>>,

create a local maximum leading into over-segmentation when tree crowns are detected by local maxima filtering. Shendryk published a eucalyptus delineation algorithm that starts segmentation from bottom to top. In this paper, the trunks point cloud is separated from the leaves and individual trunks are identified before proceeding to crown segmentation [61]. Nevertheless, for that project only 17 flightlines of LiDAR data were collected. The density resolution starts from 12 points/ m^2 and goes up to 36 points/ m^2 around forested areas. For small research projects capturing this high resolution is ok, but for commercial use and larger areas, the density of data collected is above the optimal resolution for a cost effective versus quality acquisition [62]. The project of this thesis is much larger. The resolution of our acquired LiDAR data has an average of four pulses per square meter, which is considered an optimal resolution. But because of the tree height (up to 43 meters according to the fieldwork), a small amount of pulse intensity reached the trunks and the recorded waveform do not include enough information for individual trunk detection. An example of this project's discrete LiDAR data is shown in Figure 8-2 and the missing information about the trunks is depicted.

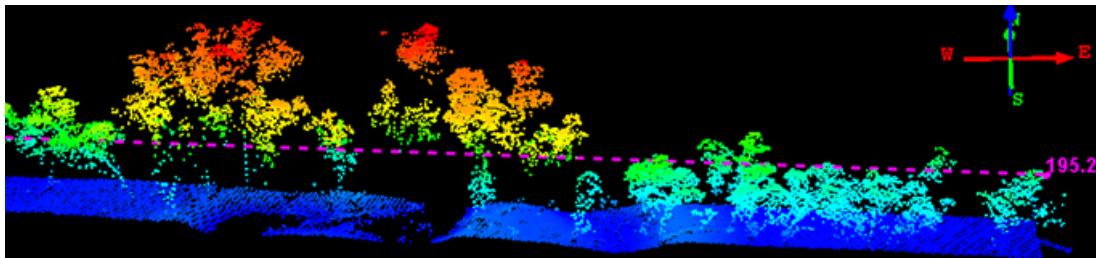


Figure 8-2: LiDAR point cloud showing that there are very limited points reflected from tree trunks.

***Note read again to make sure it matches OK

The acquired data are full-waveform LiDAR data. Traditional ways of interpreting FW LiDAR data, suggests extraction of a denser points cloud using Gaussian decomposition [15] [16]. Nevertheless, in this project we uses the open source software DASOS. DASOS was influenced by Persson et al, 2005, who used voxelisation to visualise the waveforms [20]. But, it does not only uses voxelisation for visualisations but also for extracting metrics useful in classification. It further normalises the intensities so that equal pulse length exists inside each voxel, making intensities more meaningful. It is further seems that the literature is moving towards voxelisation with promising results obtained at recent publication on tree species classification [21].

Here, it is introduced an approach for quick dead tree detection derived from the boost cascade approach [63] but extended into 3D. This approach further contains

Hollow Owl: <http://www.mariewinn.com/marieblog/uploaded_images/screech2-738532.jpg>

similarities of the 3D tree shape signatures proposed by Dong, 2009, for distinguishing Oaks from Douglas fir tree crowns [64].

8.2 Materials

In this section, information about the study area, the acquired remote sensing and field data are provided. Figure 8-3 depicts all of them on a map, while section 8.2.1, 8.2.2 and 8.2.3 give technical information about them.

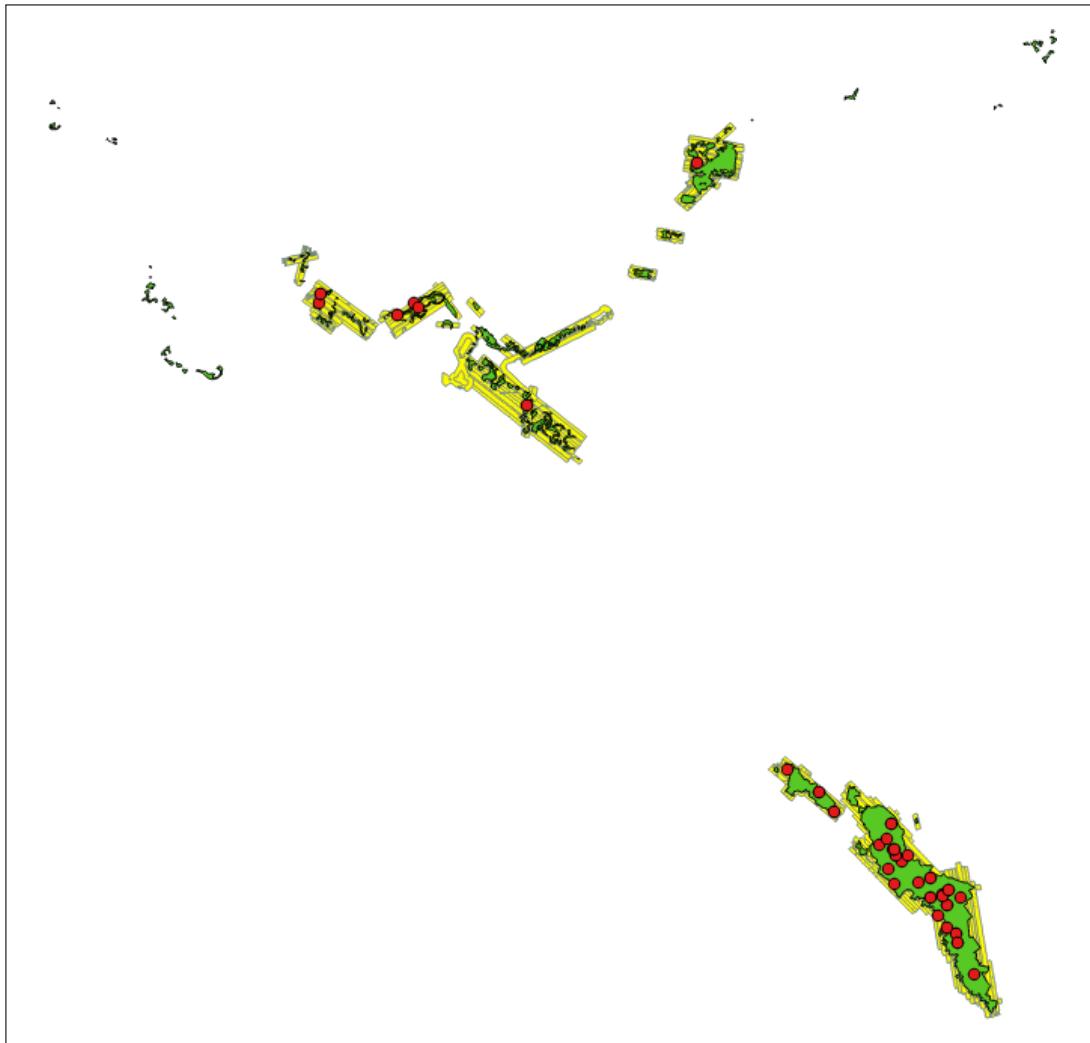


Figure 8-3: The study area is depicted by green ($542km^2$), the yellow strips are the LiDAR flightlines and the red dots are the position of the field plots. ****Note: this image many need to be removed due to confidentiality of the company. I will talk with them and hopefully it will be ok.**

8.2.1 Study Area

The study area is a native River Red Gum (*Eucalyptus camaldulensis*) forest of size 542km^2 in south-eastern Australia. The regeneration of the eucalyptus is extremely dependant in floods and therefore, their distribution in respect to density, health and age is highly variance [65]. Additionally, the height of *Eucalyptus camaldulensis* reaches up to 30-40m and their structural complexity is high with multiple trunk splits [66]. The size and structure of the forest, with a human as reference, is depicted in Figure 8-4, while examples of the variance shape of dead trees is shown in Figure 8-5.



Figure 8-4: Structure of Red Gum Forest in south-eastern Australia.

8.2.2 Acquired full-waveform LiDAR data

Multiple-echo, full-waveform (FW) LiDAR data are supplied by RPS Australia East Pty Ltd. The data were acquired from 900m above ground level, using the Trimble AX60 Airborne LiDAR sensor, which was released in October 2013 [67]. The wavelength of the emitted laser was 1062nm, the maximum scan angle was 60 degrees, and the pulse



Figure 8-5: Example of dead trees indicating their variance in shape.

rate was 400kHz. The acquisition was held from the 6th of March till the 31st of March 2015. The collected LiDAR were delivered into 206 flightlines, of which 13 are cross runs used for geometric correction. There is also a 30% of swath overlap. The point spacing along and across the track is 0.48m and the average point spacing is 4.3 points per square meter. Figure 8-6 shows an example of a dead tree in respect to the acquired discrete LiDAR point cloud. Detailed information about FW LiDAR related concepts are given in section 2.

8.2.3 Field Data

The field data were collected in July 2015 during the winter season of Australia and they include tree and canopy related measurements on circular plots. There are 33 plots with radius 35.68m and area 0.4ha allocated randomly inside the study area. On these plots, a total of 2386 trees were individually measured. Tree measurements include the geo-location, the trunk diameter at the standard height of 1.3m (breast height), height, species and health conditions (i.e. dead or alive). The geo-location of each tree is defined by the magnetic bearing from the centroid of the plot in degrees (range [1, 360]) and the distance from the centroid in meters. The northing and easting coordinates of the geo-location of each tree were calculated in post-processing. Here it worth mentioning that a single tree may be recorded as multiple trees if there is a trunk split bellow the breast height of 1.3m. Furthermore, 91.59% are River Red Gum and the rest are Black Box (*Eucalyptus largiflorens*) and Wattle group (*Acacia* spp.).

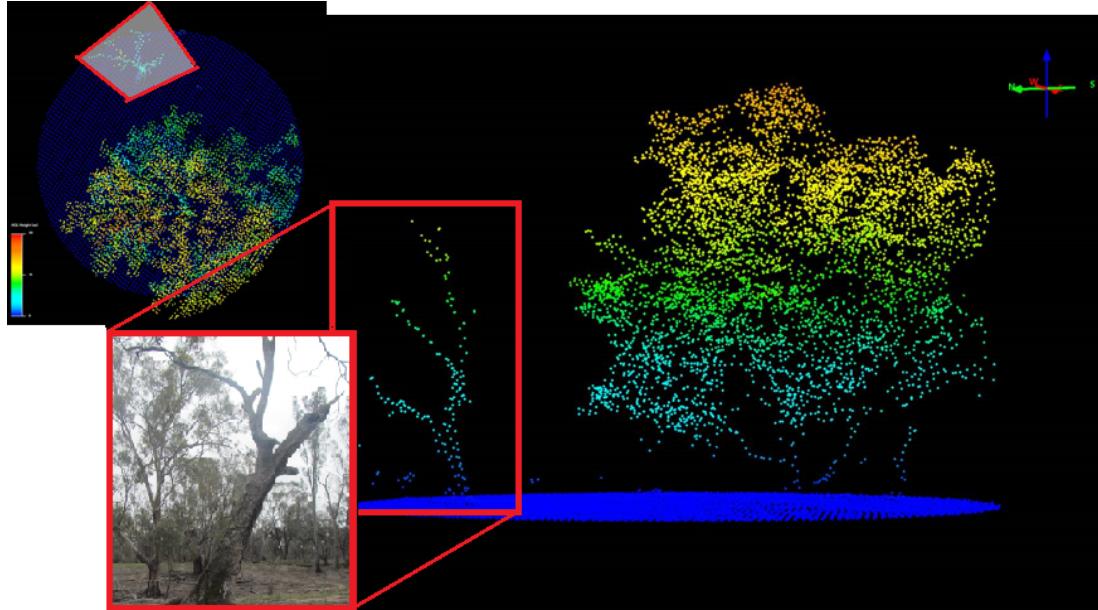


Figure 8-6: Example of a dead tree in relation to the discrete LiDAR point cloud.

Inside the field data, there are 260 dead trees recorded. Nevertheless, not all of those trees are considered useful for biodiversity. Dead trees with big Diameter at Breast Height (DBH) are more likely to contain hollows. Additionally, trees with DBH smaller than the footprint spacing of the LiDAR data are not identifiable from the FW LiDAR data. Table 8.1 shows the number of dead and alive trees in respect to their DBH.

DBH	Dead Trees	Alive Trees
>2000	0	1
1000-2000	7	21
600-1000	8	146
400-600	26	290
300-400	32	286
200-300	50	462
100-200	125	904
<100	11	16
Total	260	2126

Table 8.1: Number of trees according to their DBH. **Note: I think it is in centimeter but I will confirm it with the company and add it afterwards.

Please note that the aforementioned field data were provided by Forestry Corporation of NSW, Wauchope, Australia and Interpine Ltd Group, New Zealand. For this

thesis, a case study for collecting field data was conducted in New Forest, UK. This helped to better understand classification challenges in forestry applications. More information about this study is provided in Appendix B.

**Note: Please move to the Appendix now, because the following sections are not completed

8.3 Methods and Algorithms / Statistical Analysis

steps

- Subtract DTM From full-waveform LiDAR
- DASOS and 3D priors
- Random Forest for identifying the most significant features
- Nearest Neighbour
- Thinning Algorithm
- Remove Ground and noisy columns using Gaussian decomposition
- Evaluation

8.3.1 Subtract DTM from FW LiDAR

generating DTM beyond the scope of this research. The DTM is generated using the Quick Terrain Modeller from the discrete LiDAR using the parameters shown in Figure ??.

DASOS has a feature for subtracting the DTM from the full-waveforms before generating the volumetric representation of the data. Figure ?? shows the DEM before and after the subtraction.

8.3.1.1 DASOS and 3D priors

The 3D shape signatures were generated by getting the distance distribution of random LiDAR point pairs of the two tree crown classes: Oaks and Douglas [64]

Here it is worth mentioning that this project is the first application of the new feature of DASOS that was released on the 20th of January 2017 [68].

In this chapter, the 3rd feature of DASOS (Table 4.3) is used for generating 3D priors characterising dead standing Eucalypt trees. These 3D priors are used for detecting dead standing Eucalypt trees in native Australian forests.

like Viola but in 3D

the sets we create: 1. raw intensities

Figure 8-7

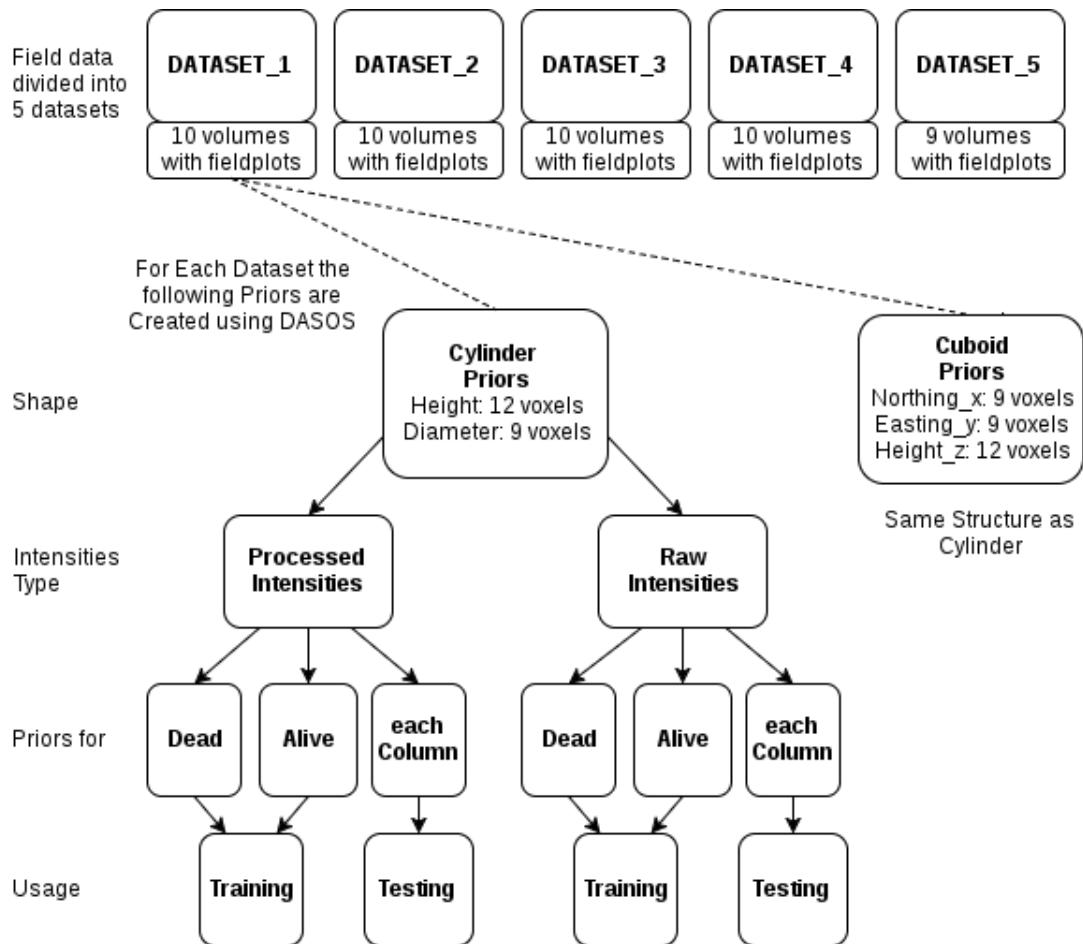


Figure 8-7: This figure shows what priors were created for testing and how they are divided for cross validation.

Explanation of the 3D priors Output with the Processed Intensities	
Label	Description
Height_Middle_Column	The height of the middle column of the prior
Height_Mean	The Mean height of all the columns included in the template
Height_Median	The Median height of all the columns included in the template
Height_Std	The Standard Deviation of the heights of the columns included in the template
Sum_Int_Diff_X	The Mirror Summed Difference of the intensities using the middle column in the x-axis as the axis of symmetry
Sum_Int_Diff_Y	The Mirror Summed Difference of the intensities using the middle column in the y-axis as the axis of symmetry
Sum_Int_Diff_Z	The Mirror Summed Difference of the intensities using the middle column in the z-axis as the axis of symmetry
Max_Int	The maximum intensity found inside the prior
Min_Int	The minimum intensity found inside the prior
Ave_Int	The average intensity of the voxels that contain an intensity above the isolevel
Median_Int	The median intensity of the voxels
Per_Int_Above_Iso	Percentage of voxels that contain an intensity above the isolevel
Dis_Mean	Mean distance from the central voxel to every voxel that contains an intensity above the isolevel
Dis_Median	Median distance from the central voxel to every voxel that contains an intensity above the isolevel
Dis_Std	The Standard Deviation of the distances between the central voxel and every voxel that contains an intensity above the isolevel
Top_Patch_Len_Middle_CoI	The length of the top patch of the middle column of the prior

Top_Patch_Len_Mean	The Mean length of all the top patches
Top_Patch_Len_Median	The Median length of all the top patches
Top_Patch_Len_Std	The Standard Deviation of all the top patches
Mirror_Diff_X_Mean	The Mean Mirror Difference of the voxel intensities with the middle column of the x-axis as the symmetric axis
Mirror_Diff_X_Median	The Median Mirror Difference of the voxel intensities with the middle column of the x-axis as the symmetric axis
Mirror_Diff_X_Std	The Standard Deviation Mirror Difference of the voxel intensities with the middle column of the x-axis as the symmetric axis
Mirror_Diff_Y_Mean	The Mean Mirror Difference of the voxel intensities with the middle column of the y-axis as the symmetric axis
Mirror_Diff_Y_Median	The Median Mirror Difference of the voxel intensities with the middle column of the y-axis as the symmetric axis
Mirror_Diff_Y_Std	The Standard Deviation Mirror Difference of the voxel intensities with the middle column of the y-axis as the symmetric axis
Mirror_Diff_Z_Mean	The Mean Mirror Difference of the voxel intensities with the middle column of the z-axis as the symmetric axis
Mirror_Diff_Z_Median	The Median Mirror Difference of the voxel intensities with the middle column of the z-axis as the symmetric axis
Mirror_Diff_Z_Std	The Standard Deviation of the Mirror Difference of the voxel intensities with the middle column of the z-axis as the symmetric axis

Table 8.2: The three functionalities of DASOS

In the following section, the images and examples are taken from the Cylinder processed parameters but it done for all four test cases and cross validated using the 5 datasets division.

8.3.2 Random Forest

Images and examples for Cylinder processed parameters but it done for all four test cases and cross validated using the 5 datasets division.

Random Forest failed to find relation between the 3D priors with the Raw Intensities due to the irregular shapes of Eucalyptus trees and probably due to the scan from different angles. Raw Intensities may be useful for identifying pine trees in commercial forest, where the variance between each other is smaller.

Therefore from here we only test processed intensities with 3D cylindrical and 3D rectangular cuboid priors.

Identified the most significant features for detecting dead trees and then we build the following probabilistic model.

8.3.3 Probabilistic Model

We don't go straight to classification because in the testing data, we put a prior for each column and therefore many columns that contain dead trees are not marked correctly. And we wrote a probabilistic model using the most significant features identified by the random forest.

k-nearest neighbour: distance from the centre of mean for each of the first 5 significant features

from that get grey scale field of the results

8.3.4 Filtering and Local Maxima

Salt and pepper filter

Smoothing filter

Once the probability field is created, we smooth the image and detect the local maxima.

8.3.5 Ground Mask

Great histogram of the height map generated using the 2D metrics of DASOS.

Create three classes : ground, trees and noise

Because the DTM has been subtracted (Section 8.3.1), the ground is easily separated from the trees.

Mask out ground and noise

8.3.6 Threshold

if a local maxima is found but the probability of being a dead is low then it is not a dead tree. This is defined by a user defined constant threshold.

8.4 Results

8.5 Discussion

Chapter 9

Overall Results

Chapter 10

Conclusions

10.1 Contributions

Bibliography

- [1] R. B. Smith, *Introduction to Hyperspectral Imaging*. MicroImages, 2014.
- [2] W. Wanger, A. Ullrich, T. Melzer, C. Briese, and K. Kraus, “From single-pulse to full-waveform airborne laser scanners,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 60, pp. 100–112, 2004.
- [3] A. Wehr and U. Lohr, “Airborne laser scanning - an introduction and overview,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 54, pp. 68–82, 1999.
- [4] C. Mallet and F. Bretar, “Full-waveform topographic lidar: State-of-the-art,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 64, pp. 1–16, 2009.
- [5] K. Anderson, S. Hancock, M. Disney, and K. Gaston, “Is waveform worth it? a comparison of lidar approaches for vegetation and landscape characterization,” *Remote Sensing in Ecology and Conservation*, 2015.
- [6] A. Chauve, C. Mallet, F. Bretar, S. Durrieu, M. Deseilligny, and W. Puech, “Processing full-waveform lidar data: Modelling raw signals,” *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2007.
- [7] *LAS Specification version 1.3-R1*. Bethesda, Maryland: American Society for Photogrammetry and Remote Sensing, 2010.
- [8] M. Warren, *Full Waveform Upgrade*. NERC ARSF wiki, 2012.
- [9] M. J. Sumnall, R. A. Hill, and S. A. Hinsley, “Comparison of small-footprint discrete return and full waveform airborne lidar data for estimating multiple forest variables,” *Remote Sensing of Environment*, vol. 173, pp. 214–223, 2016.
- [10] K. H. R. A. Z. A. Lehner, H., “Consideration of laser pulse fluctuations and automatic gain control in radiometric calibration of airborne laser scanning data.,” *Proceedings of 6th ISPRS Student Consortium and WG VI/5 Summer School*, 2011.

- [11] I. Korpela, H. O. Ørka, H. V. Hyppä, J., and T. Tokola, “Range and agc normalization in airborne discrete-return lidar intensity data for forest canopies,” vol. 65, no. 4, pp. 369–379, 2010.
- [12] M. Isenburg, *LAStools - efficient tools for LiDAR processing*. rapidlasso.
- [13] M. Warren, B. Taylor, M. Grant, and J. D. Shutler, “Data processing of remorely sensed airborne hyperspectral data using the airborne processing library (apl),” *ScienceDirect, Computers and Geosciences*, vol. 64, 2014.
- [14] W. Wanger, A. Ullrich, V. Ducic, T. Maizer, and N. Studnicka, “Gaussian decompositions and calibration of a novel small-footprint full-waveform digitising airborne laser scanner,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 60, pp. 100–112, 2006.
- [15] A. Neuenschwander, L. Magruder, and M. Tyler, “Landcover classification of small-footprint full-waveform lidar data,” *Jounal of Applied Remote Sensing*, vol. 3, no. 1, pp. 033544–033544.
- [16] J. Reitberger, P. Krzystek, and U. Stilla, “Analysis of full waveform LiDAR data for tree species classification,” *International Journal of Remote Sensing*, vol. 29, no. 5, pp. 1407–1431, 2008.
- [17] M. Isenburg, “Pulsewaves: An open, vendor-neutral, stand-alone, las-compatible full waveform lidar standard.,” 2012.
- [18] A. Chauve, F. Bretar, S. Durrieu, M. Pierrot-Deseilligny, and W. Puech, “Fullanalyse: A research tool for handling, processing and analysing full-waveform lidar data,” *IEEE International Geoscience and Remote Sensing Symposium*, 2009.
- [19] P. Bunting, J. Armston, D. Clewley, and R. M. Lucas, “Sorted pulse data (spd) library—part ii: A processing framework for lidar data from pulsed laser systems in terrestrial environments,” *Computers & Geosciences*, vol. 56, pp. 207–215, 2013.
- [20] A. Persson, U. Soderman, J. Topel, and S. Ahlberg, *Visualisation and Analysis of full-waveform airborne laser scanner data*. V/3 Workshop, Laser scanning 2005, 2005.
- [21] L. Cao, N. Coops, L. Innes, J. Dai, and H. Ruan, “Tree species classification in subtropical forests using small-footprint full-waveform lidar data,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 49, pp. 39–51, 2016.

- [22] S. Hancock, K. Anderson, M. Disney, and K. J. Gaston, “Measurement of fine-spatial-resolution 3d vegetation structure with airborne waveform lidar: Calibration and validation with voxelised terrestrial lidar.,” *Remote Sensing of Environment*, vol. 188, pp. 37–50, 2017.
- [23] M. Miltiadou, M. Grant, M. Brown, M. Warren, and E. Carolan, “Reconstruction of a 3d polygon representation from full-waveform lidar data,” *RSPSoc Annual Conference 2014, New Sensors for a Changing World*, 2014.
- [24] M. Miltiadou, M. A. Warren, M. Grant, and M. Brown, “Alignment of hyperspectral imagery and full-waveform lidar data for visualisation and classification purposes,” *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 40, no. 7, p. 1257, 2015.
- [25] R. Crippen, “Calculating the vegetation index faster,” *Remote Sensing of Environment*, vol. 34, no. 1, pp. 71–73, 1990.
- [26] R. N. Clark, G. A. Swayze, R. Wise, K. E. Livo, T. Hoefen, R. F. Kokaly, and S. J. Sutley, “Usgs digital spectral library splib06a,” *US Geological Survey, Digital Data Series*, vol. 231, 2007.
- [27] P. Hanrahan, “Ray tracing algebraic surfaces,” *ACM SIGGRAPH Computer Graphics*, vol. 17, no. 3., 1983.
- [28] H. Pfister, J. Harderbergh, J. Knittel, H. Lauer, and L. Seiler, “The volumepro real-time ray-casting system,” *Proceedings of the 26th annual conference on Computer graphics and interactive techniques*, pp. 251–260, 1999.
- [29] J. Nickolls, I. Buck, M. Garland, and K. Skadron, “Scalable parallel programming with cuda,” *Queue*, vol. 6, no. 2, pp. 40–55, 2008.
- [30] C. Crassin, F. Neyret, S. Lefebvre, and E. Eisemann, “Gigavoxels: Ray-guided streaming for efficient and detailed voxel rendering,” *Proceedings of the 2009 symposium on Interactive 3D graphics and games*, pp. 15–22, 2009.
- [31] J. F. Blinn, *A Generalization of Algebraic Surface Drawing*, vol. 1. ACM Transactions on Graphics (TOG).
- [32] A. Pasko and V. Savchenko, *Blending operations for the functionally based constructive geometry*. 1994.

- [33] W. E. Lorensen and H. E. Cline, “Marching cubes: A high resolution 3d surface construction algorithm,” *ACM Siggraph Computer Graphics*, vol. 21, pp. 163–169, 1987.
- [34] M. L. Clark, D. A. Roberts, J. J. Ewel, and D. B. Clark, “Estimation of tropical rain forest aboveground biomass with small-footprint lidar and hyperspectral sensors,” *ScienceDirect, Remote Sensing of Environment*, vol. 115.
- [35] J. E. Anderson, L. C. Plourde, M. E. Martin, B. H. Braswell, M. L. Smith, R. O. Dubayah, M. A. H. Dubayah, and J. B. Blair, “Integrating waveform lidar with hyperspectral imagery for inventory of a northern temperate forest,” *Remote Sensing of Environment*, vol. 112, no. 4, pp. 1856–1870, 2008.
- [36] H. Buddenbaum, S. Seeling, and J. Hill, “Fusion of full-waveform lidar and imaging spectroscopy remote sensing data for the characterization of forest stands,” *International Journal of Remote Sensing*, vol. 32, no. 13, pp. 4511–4524, 2013.
- [37] J. Heinzel and B. Koch, “Investigating multiple data sources for tree species classification in temperate forest and use for single tree delineation,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 18, pp. 101–110, 2012.
- [38] R. G. Congalton, “A review of assessing the accuracy of classifications of remotely sensed data,” *Remote Sensing of Environment*, vol. 37, no. 1.
- [39] J. F. Franklin, H. H. Shugart, and M. E. Harmon, “Tree death as an ecological process,” *BioScience*, vol. 17, no. 8, pp. 550–556, 1987.
- [40] J. Siitonens, “Forest management, coarse woody debris and saprophytic organisms: Fennoscandian boreal forests as an example,” *Ecological bulletins*, pp. 11–41, 2001.
- [41] I. Hanski, “Extinction debt and species credit in boreal forests: modelling the consequences of different approaches to biodiversity conservation,” *Annales Zoologici Fennici*, pp. 271–280, 2000.
- [42] G. Peterson, C. R. Allen, and C. S. Holling, “Ecological resilience, biodiversity, and scale.,” *Ecosystems*, vol. 1, no. 1, pp. 6–18, 1998.
- [43] N. Abrego and I. Salcedo, “How does fungal diversity change based on woody debris type? a case study in northern spain,” *Ekologija*, vol. 57, no. 3, 2011.

- [44] J. N. Stokland and K. H. Larsson, “Legacies from natural forest dynamics: Different effects of forest management on wood-inhabiting fungi in pine and spruce forests,” *Forest Ecology and Management*, vol. 261, no. 11, pp. 1707–1721, 2011.
- [45] D. Lonsdale, M. Pautasso, and O. Holdenrieder, “Wood-decaying fungi in the forest: conservation needs and management options,” *European Journal of Forest Research*, vol. 127, no. 1, pp. 1–22, 2008.
- [46] P. Gibbons and D. Lindenmayer, *Tree Hollows and Wildlife Conservation in Australia*. CSIRO Publishing, 2002.
- [47] D. B. Lindenmayer and J. T. Wood, “Long-term patterns in the decay, collapse, and abundance of trees with hollows in the mountain ash (eucalyptus regnans) forests of victoria, southeastern australia,” *Canadian Journal of Forest Research*, vol. 40, no. 1, pp. 48–54, 2010.
- [48] R. L. Goldingay, “Characteristics of tree hollows used by australian birds and bats,” *Wildlife Research*, vol. 36, no. 5, pp. 394–409, 2009.
- [49] “List of extinct, threatened and near threatened australian birds,” *Environment Protection and Biodiversity Conservation Act*, 1999.
- [50] Government of Western Australia, “Oarks and wildlife the list of threatened and priority fauna list,” tech. rep., November 2015.
- [51] Y. Kim, Z. Yang, W. B. Cohen, D. Pflugmacher, C. L. Lauver, and J. L. Vankat, “Distinguishing between live and dead standing tree biomass on the north rim of grand canyon national park, usa using small-footprint lidar data.,” *Remote Sensing of Environment*, vol. 113, no. 11, pp. 2499–2510, 2009.
- [52] P. Polewski, W. Yao, M. Heurich, P. Krzystek, and U. Stilla, “Detection of fallen trees in als point clouds using a normalized cut approach trained by simulation,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 105, pp. 252–271, 2015.
- [53] W. Mücke, B. Deák, H. M. Schroiff, A., and N. Pfeifer, “Detection of fallen trees in forested areas using small footprint airborne laser scanning data,” *Canadian Journal of Remote Sensing*, vol. 139, no. s1, pp. S32–S40, 2013.
- [54] W. Yao, P. Krzystek, and M. Heurich, “Identifying standing dead trees in forest areas based on 3d single tree detection from full-waveform lidar data,” *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. I-7, pp. 359–364, 2012.

- [55] J. Pasher and D. J. King, “Mapping dead wood distribution in a temperate hard-wood forest using high resolution airborne imagery,” *Forest Ecology and Management*, vol. 258, no. 7, pp. 1536–1548, 2009.
- [56] I. Shendryk, M. Broich, M. G. Tulbure, A. McGrath, D. Keith, and S. V. Alexandrov, “Mapping individual tree health using full-waveform airborne laser scans and imaging spectroscopy: A case study for a floodplain eucalypt forest,” *Remote Sensing of Environment*, vol. 187, pp. 202–217, 2016.
- [57] S. C. Popescu, R. H. Wynne, and R. F. Nelson, “Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass,” *Canadian journal of remote sensing*, vol. 29, no. 5, pp. 564–577, 2003.
- [58] L. Jing, B. Hu, J. Li, and T. Noland, “Automated delineation of individual tree crowns from lidar data by multi-scale analysis and segmentation,” *Photogrammetric Engineering & Remote Sensing*, vol. 78, no. 12, pp. 1275–1284, 2012.
- [59] B. Hu, J. Li, L. Jing, and A. Judah, “Improving the efficiency and accuracy of individual tree crown delineation from high-density lidar data,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 26, pp. 145–15, 2014.
- [60] S. C. Popescu and K. Zhao, “A voxel-based lidar method for estimating crown base height for deciduous and pine trees,” *Remote sensing of environment*, vol. 112, no. 3, pp. 767–781, 2008.
- [61] I. Shendryk, M. Broich, M. G. Tulbure, and S. V. Alexandrov, “Bottom-up delineation of individual trees from full-waveform airborne laser scans in a structurally complex eucalypt forest,” *Remote Sensing of Environment*, vol. 173, pp. 69–83, 2016.
- [62] J. L. Lovell, D. L. B. Jupp, G. J. Newnham, N. C. Coops, and D. S. Culvenor, “Simulation study for finding optimal lidar acquisition parameters for forest height retrieval.,” *Forest Ecology and Management*, vol. 214, no. 1.
- [63] P. Viola and M. Jones, “Rapid object detection using a boosted cascade of simple features,” *Computer Vision and Pattern Recognition*, vol. 1, 2001.
- [64] P. Dong, “Characterization of individual tree crowns using three-dimensional space signatures derived from lidar data.,” *International Journal of Remote Sensing*, vol. 30, no. 24, pp. 6621–6628, 2009.
- [65] J. Kerle, “Collation and review of stem density data and thinning prescriptions for the vegetation communities of new south wales,” 2005.

- [66] N. Wilson and N. C. C. of N.S.W, “The flooded gum trees : land use and management of river red gums in new south wales,” *The Council, Sydney*, 1995.
- [67] E. van Rees, “Trimble’s ax60i and ax80,” *GeoInformatics*, vol. 7, no. 5.
- [68] M. Miltiadou, N. D. F. Campbell, M. Brown, A. S. G., M. Warren, D. Clewley, and M. Grant, “User guide of the 2nd version o dasos,” 2017.

Appendix A

DASOS user guide

Appendix B

Case Study: Field Work in New Forest