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

submitted by

Milto Miltiadou

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and of the

Plymouth Marine Laboratory

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Abstract

no more than 300 words

NOTES:

Blue colour: additions according to Neill's feedback,

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	($\delta\alpha\sigma o\varsigma$=forest in Greek), the open source software implemented for managing FW LiDAR data
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

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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.

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Awards

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.

Conference Presentations

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 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 [1]. As an indication, more than 4000 species inhabit dead wood in Finland [2], where an estimate of 1000 species has been extinct [3]. 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 [4]. Observing the changes of fungal diversity on decaying wood has an increased interest in science [5] [6] [7] 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 [8]. 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 [9] [10]. 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 [11] [12]. 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 [13]. 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 [14] [15]. Regarding standing dead trees, their shape (reduced number of leaves or broken branches) [16] and light reflectance (less green light illuminated) [17] are important factors for identifying them.

Previous work on dead standing trees detection performs single tree crown delineation before health assessment [16] [18].Tree-crown delineation is usually done by detecting local maxima from the canopy height model (CHM) and then segmenting trees with watershed algorithm [19]. Improvements has been achieved by introducing markers controlled watershed [20] and structural elements of tree crowns with different sizes [21]. Additionally, Popescu and Zhao analyse the vertical distribution of the LiDAR points in conjunction with the local maximum filtering of CHM [22].

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 Ow, Barking Owl, **Masked Owl**, **Barn Owl**, White-throated Treecreeper, Hollow Owl, **Brush-tailed Possum** (mammal) [1]

[1] The 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://aussiegal7.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/AAAAAAAAAWg/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: <ttp://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 [23]. Nevertheless, there is the consideration of optimal resolution for a cost effective versus quality acquisition [24]. For this project, there is an average of four pulses per square meter, which is considered an optimal resolution. But because of the tree height (up to 43meters according to the fieldwork), a small amount of pulse intensity reached the trunks and the recordered 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 are depicted.

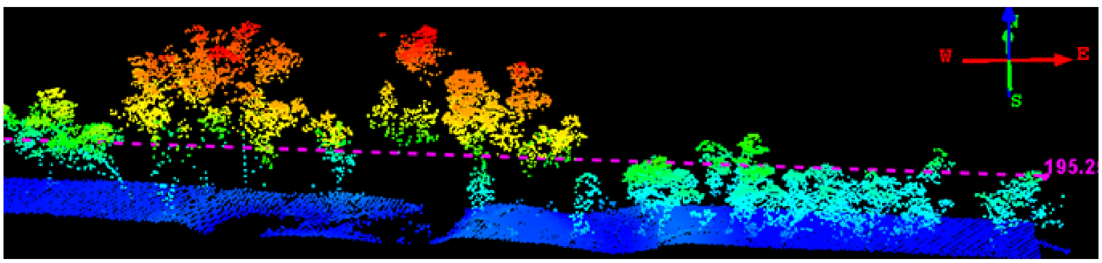

Figure 8-2: LiDAR point cloud showing that there are very limited points reflected from tree trunks.

Here, it is introduced an approach for quick dead tree detection derived from the boost cascade approach [25] but extended into 3D. This approach further contains similaries of the 3D tree shape signatures proposed by Dong, 2009, for distinguishing Oaks from Douglas fir tree crowns [26].

8.2 Materials and Methods

8.2.1 Study Area

The study area is a native River Red Gum (Eucalyptus camaldulensis) forest in south-eastern Australia and its size is $542 km^2$. The regeneration of the eucalyptus is highly depended and therefore, their distribution in respect to density, health and age is highly variance [27]. Additionally, the height of Eucalyptus camaldulensis reaches up to 30-40m and their structural complexity is high with multiple trunk splits [28].

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

Figure 8-3: The shape of dead trees significantly varies from the each other. Here there is an example of two dead trees.

8.2.2 Acquired full-waveform LiDAR data

For this project, FW LiDAR data has been acquired. The data were supplied by RPS Australia East Pty Ltd and they were collected in March 2015 using the Trimble AX60 Airborne LiDAR sensor.

8.2.3 Field Data

33 plots allocated randomly in the area of interest Plot Radius: 35.68m GPS tree location Tree information like Dead trees 2386 Trees 269 Dead Trees

In addition, the field plots used for the classifications are provided by (Interprine Group Ltd or Forest Corporation?) and contain around 1000 Eucalypt trees while 10% of them are dead.

8.2.4 Statistical Analysis

8.2.4.1 The 3D-priors feature of DASOS

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 [26]

In this chapter, the 3rd feature of DASOS (Table **??**) 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.

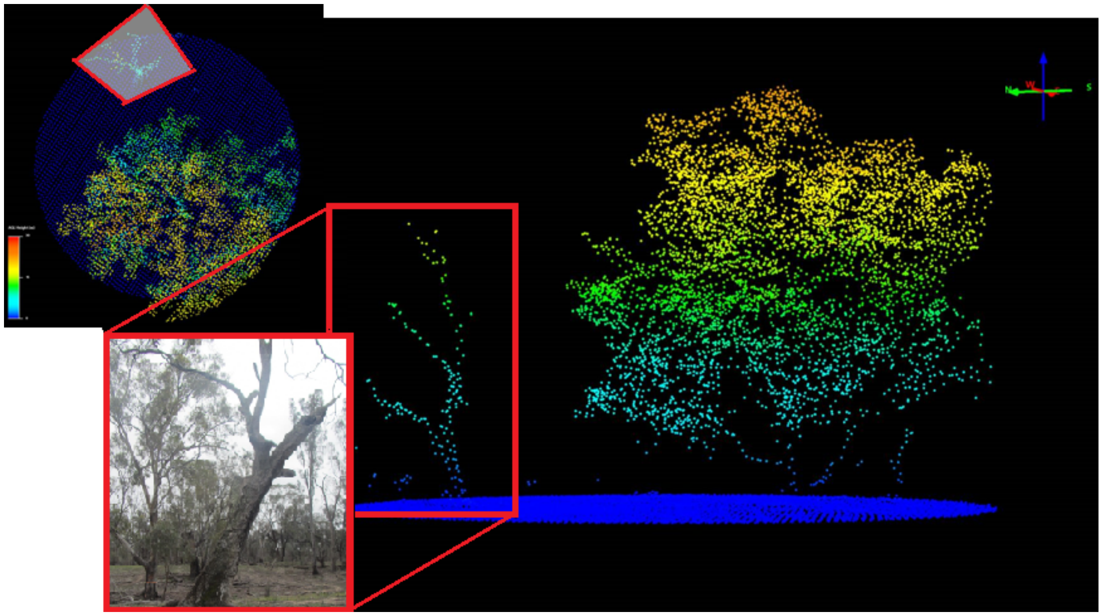

Figure 8-4: Example of a dead tree in relation to the discrete LiDAR point cloud.

8.3 Results

8.4 Discussion

Chapter 9

Comparison with Discrete Data

Furthermore, DASOS allows the user to choose whether the waveform samples or the discrete returns are inserted into the 3D density volume. Each sample or each return has a hit point and an intensity value. So, in both case the space is divided into 3D voxels and the intensity of each return or sample is inserted into the voxel it lies inside.

In general the results of discrete returns contain less information compared to the results from the FW LiDAR, even though the FW LiDAR contain information from about half of the emitted pulses (Section 3). As shown on the 1st example of table 3 the polygon mesh generated from the FW LiDAR contains more details comparing to the one created from the discrete LiDAR. The forest on the top is more detailed, the warehouses in the middle have a clearer shape and the fence on the right lower corner is continuous while in the discrete data it is disconnected and merged with the aliasing.

FW LiDAR polygons, compared to the discrete LiDAR ones, contain more geometry below the outlined surface of the trees. On the one hand this is positive because they include much information about the tree branches but on the other hand the complexity of the objects generated is high. A potential use of the polygon representations is in movie productions: instead of creating a 3D virtual city or forest from scratch, the area of interest can be scanned and then polygonised using our system.

But for efficiency purposes in both animation and rendering, polygonal objects should be closed and their faces should be connected. Hence, in movie productions, polygons generated from the FW LiDAR will require more post-processing in comparison with object generated from the discrete LiDAR.

Example 2 in table 3 shows the differences in the geometry complexity of the discrete and FW polygons using the x-ray shader of Meshlab. The brighter the surface appears the more geometry exists below the top surface. The brightness difference between area 1 and area 2 appears less in the discrete polygon.

Nevertheless, the trees in area 2 are much taller than in area 1, therefore more geometry should have existed in area 2 and sequentially be brighter. But the two areas are only well-distinguished in the FW LiDAR. On average the FW polygon is brighter than the discrete polygon, which implies higher geometry complexity in the FW polygon.

The comparison example 3 is rendered using the Radiance Scaling shader of Meshlab (Vergne et al, 2010). The shader highlights the details of the mesh, making the comparison easier. Not only the FW polygons are more detailed but also holes appear on the discrete polygons. The resolution of the voxels of those examples is 1.7m3 is, the bigger the holes are, while the full-waveform can be polygonised at a resolution of 1m3 without any significant holes. Figure 4 shows an example of rendering the same flightline of examples 3 at the resolution of 1m3 LiDAR data.

The last two examples (4 and 5) compare the side views of small regions. On the one hand the top of the trees are better-shaped in the discrete data. This may occur either because the discrete data contain information from double pulses than the FW data (Section 3) or because the noise threshold of the waveforms is not accurate and the top of the trees appear noisier on the FW LiDAR data. On the other hand more details appear close to the ground on the FW LiDAR data.

*** left during copying :s (and the higher the resolution, using FW)

Chapter 10

Overall Results

Chapter 11

Conclusions

11.1 Contributions

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Appendix A

DASOS user guide

Appendix B

Case Study: Field Work in New Forest

B.1 Introduction

This section is a case study containing field work from a non-professional perspective to better understand the challenges of working remotely with forests. Remotely sensed data contain a great amount of information but in order to build a good system for identifying trees and materials, an in depth knowledge of them is required [29]. For that reason, this case study was created; information about the New Forest, which is a forest in the south of United Kingdom, were collected and a small validation dataset was created. The dataset created includes the tree species and approximate heights of the trees in two areas of interest.

Before travelling to the New Forest, two areas of interest were selected. These areas were selected according to the following criteria:

- There were LiDAR data of the selected area to be able to compare what we can see in real life with the scanned data
- Areas that had a variation of tree species were selected. This was done according to the (non-validated) results of a thesis of Bournemouth University that classified the tree species of the New Forest [30]. This helped get a broader range of tree species.

The following sections give a detailed description of the information gathered during the trip. This includes the species and height maps generated, the different types of landscapes found and the challenges faced.

B.2 Validation Data Collected

The tree classes were initially defined by the provided Bournemouth thesis [30]. A colour was chosen for each tree class and, while being in the New Forest, the aim was to mark each tree on the paper map with the corresponding colour. Using QGIS (Quantum Geographic Information System) the classification results of the forest assessment, undertaken by Sumnall in 2013 [30], were coloured with the same colours to ease comparison.

At the aforementioned forest assessment, there were 26 classes from 14 different species; the remaining 12 classes were young versions of the 14 species. Here the classes are reduced to 14 by merging all the young trees into the tree species classes (in the 4 years gap between the 2010 assessment and and the visit to new Forest in 2014, the young trees would have aged). See table B.1 for the initial 14 classes. Nevertheless, more tree species existed in the areas of interest in New Forest than those 14 classes. The colours and symbols of the extra tree classes are shown on table B.2.

Tree	Colour
1. Beech	
2. Oak	
3. Silver Birch	
4. Sweet Chestnut	
5. Corsican Pine	
6. Coast Redwood	
7. Douglas Fir	
8. Grand Fir	
9. Japanese Larch	
10. Lawson Cypress	
11. Norway Spruce	
12. Scots Pine	
13. Western Hemlock	
14. Common Adler	

Table B.1: Colours of the initial 14 classes

During the visit, tree species maps were generated for a few square meters. The position of the trees were found relative to easily-spotted refereence points (e.g. road crossing) that were marked in advanced. That was done because, according to Dr. Ross Hill, no GPS can be accurate enough when trees are around since the satellite signal bounces off the leaves and reduces the positioning accuracy. In professional fieldwork, a total station is used but, for the purposes of this visit, it was not considered necessary. By the end of the case study, ground maps were coloured according to the tree species

Tree	Colour / Symbols
15. Ash	A
16. Hawthorn	Blue pen colour
17. Malus (Crabapple)	Highlighter
18. Holly Tree	
19. Trees that have been cut down	x
20. Trees that are mixed together	// (added on top of the normal colour)

Table B.2: Classes that were added during the trip

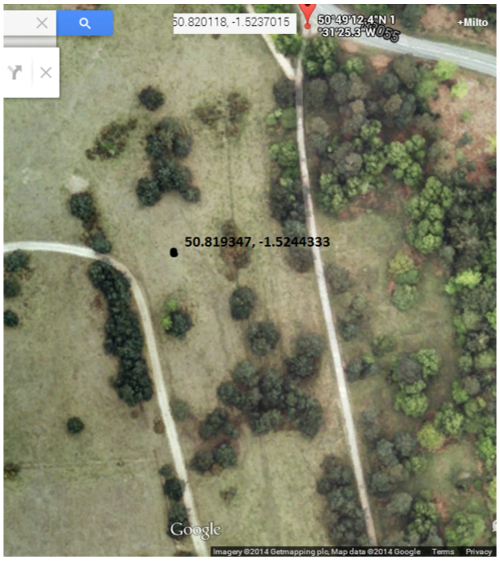
identified and estimates of the approximate heights of the trees were also noted down.

The following four maps were created for each selected area. The first two maps were created before the trip during preparation, while the last two contain the information collected during the field work.

- a screen shot of the area from Google map,
- the classification results from the forest assessment [30],
- the coloured tree species map and
- the approximated height map.

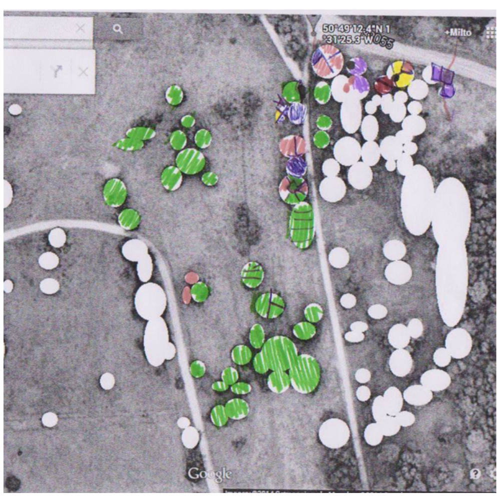
Comparing the validation dataset created with the classifications done at Bournemouth University (which were not validated), it is clear there are misclassifications. This is shown in Figures B-1 and B-2 and it is likely that is occurs due to the over-segmentation of trees. Those wrong classifications justify that validation and field work data are essential for building a good classifier.

The first area is included in the LAS file named LDR-FW-FW10_01-201018715.LAS and it lies inside the limits: X = (433453 - 433761), Y = (102193 - 102405) [British National Grid coordinates]. The four maps that relate to these areas are shown in Figure B-1.



(a) Google map screenshot

(b) Forest assessment classifications



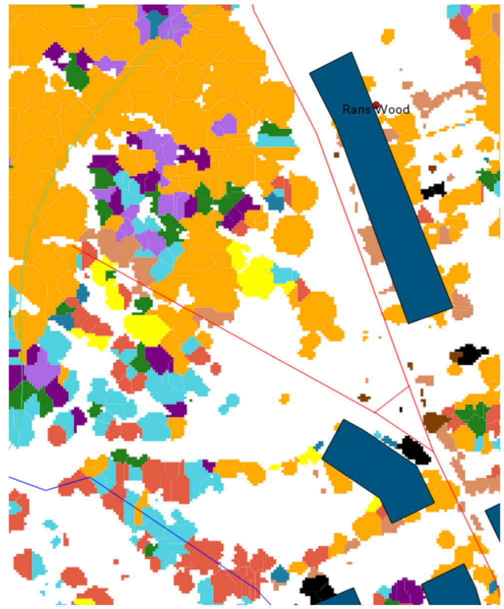
(c) Tree species map, from field work

(d) Approximate heights of the trees, from field work

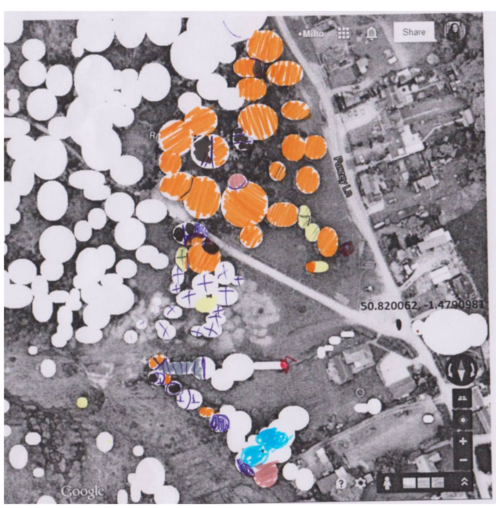
Figure B-1: The first area of interest and the related maps.

The second area is included in the LAS files named LDR-FW-FW10_01-201018719.LAS and LDR-FW-FW10_01-201018718.LAS and it lies inside the limits: X = (436442 - 436835), Y = (102334 - 102585) [British National Grid coordinates]. The four maps created for these areas are shown in Figure B-2.

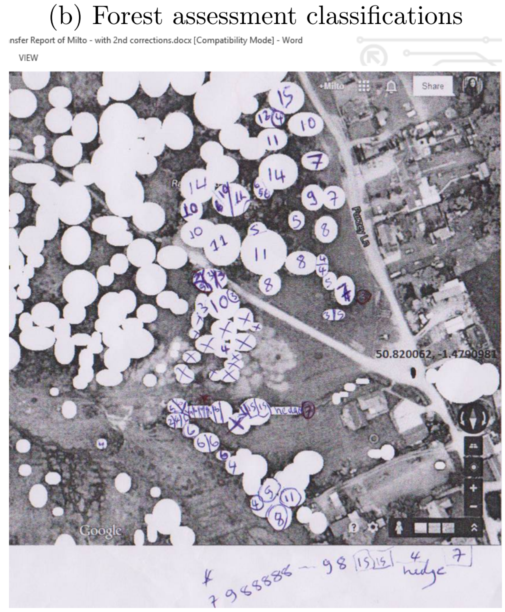
(a) Google map screenshot



(b) Forest assessment classifications



(c) Tree species map, from field work



(d) Approximate heights of the trees, from field work

Figure B-2: The second area of interest and the related maps.

- > Wrong classification due to over segmentation of the trees.

B.3 Landscape types

During the forest assessment in New Forest, not only validation data were collected, but also useful information about classifying the data. The following images show examples of the five landscape types that were found in New Forest:

1. Heather fields:

Figure B-3: Trees that have been cut down

2. Grass with a few scattered trees:

Figure B-4: Grass with a few scattered trees

3. Dense Forest:

Figure B-5: Dense forest

4. Bushes and Shrubs

Figure B-6: Trees that have been cut down

5. Lakes and rivers, which are more rarely found

Figure B-7: Lakes and rivers

Please note that the landscape types could significantly differ according to the scanned area. For example, the landscape of New Forest is flat while the landscape of Eaves Wood (another scanned forest in UK) is hilly. The landscape type should be taken into consideration during classifications.

B.3.1 Classification challenges

This case study brought further understanding of the challenges of creating validation data and writing a tree species classifier. These challenges are listed and explained below with some photos taken during field work:

1. Field work and remotely sensed data collection should happen around the same time to avoid changes that happens over time. In the New Forest case, the airborne data were collected in 2010 and many changes occurred in the intervening time - in the most extreme cases, some trees had been cut down.

2. Machine learning becomes more challenging as the number of classes increases. Regarding tree species classes, it is unrealistic to expect that all tree species will be identified. This point is underlined by the fact that the list of tree species used in the

Figure B-8: Trees that have been cut down

tree assessment held by Sumnall [30] didn't include a number of trees (e.g. holly trees and crabapple) that were widespread in New Forest.

3. There is much more than just trees in the forest, including mobile animals, that may confuse a classification if LiDAR returns hit rocks, animals, vehicles or buildings instead of branches, leaves and trunks. Any classification must account for inevitable errors due to non-target objects being in the scene.

Figure B-9: Animals in New Forest

4. Large validation datasets from a single area will not be sufficient, because trees of the same species are usually gathered together. For instance, the first selected area has many pine trees while the second one has many oak trees. Therefore, it is important to have many field plots spread well within the area of interest.

5. Further, some trees are entwined together which makes it difficult to identify from the data whether they are one or two trees. Examples are shown in Figure B-10; in the left image, the trunks of the two trees are very close to each other and, in the right image, a crabapple and an oak tree have grown together.

Figure B-10: Trees, which are mixed together

B.4 Conclusions and Discussion

To sum up, the trip to the New Forest was essential for better understanding the challenges of remote monitoring of forests. During the visit, a small validation dataset was generated; the species and height of trees that are inside the two areas of interest were noted down. Field work is a time consuming task and weeks are required for generating a big enough validation dataset, but it is essential for understanding the object of interest (trees) in relation to the scanned data. Challenges identified were also explained and this increased knowledge about forests should lead to implementing a better classifier.