Investigating the Structural Condition of Individual Trees using LiDAR Metrics

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Summary: Unlike other investigations that use discrete return (DR) light detection and ranging (LiDAR) data for the visualisation and investigation of physical structure, this research attempts to investigate data relationships found within the LiDAR point cloud in order to infer the condition of the subject of interest, which for the purposes of this investigation are tree canopies. During DR LiDAR data capture, a laser pulse is emitted from the scanner and information about the subject is captured at only at specific points known as laser returns (r). Subsequently, not all of the laser waveform is recorded, meaning that although a general impression of the subject is captured in a point cloud, there will be areas of the subject between each data point that remain unrepresented in the dataset. This paper outlines preliminary research into attempting to discover what range of LiDAR metrics, and resulting data relationships, are the most suitable to identify the significance of the structural condition of tree canopies from a tree health perspective. This research contributes to a wider investigation of automated tree health assessment and the early identification of structural failure in trees using remote sensing techniques.

Key words: LiDAR, metrics, tree canopies, tree structure, remote sensing,

Introduction

Light detection and ranging (LiDAR) is commonly used as a primary survey method for high spatial resolution investigations that assess the characteristics and 3-D structure of vegetation, in particular of forest stands and individual tree canopies (Lim, Treitza et al. 2003, Falkowski, Evans et al. 2009). LiDAR has also been used in the estimation of structural parameters of trees and other vegetation and to enable the characterisation of the forested landscape at a wide range of scales (Falkowski, Evans et al. 2009, van Leeuwen and Nieuwenhuis 2010). Data is often captured from an aerial laser scanning (ALS) platform or from either static or mobile terrestrial laser scanning (TLS) platforms. The captured data can subsequently be classified as either discrete return (DR) small-footprint LiDAR which records the elevation of a specified number of peaks in the return waveform, or full waveform (FW) LiDAR which records the returning LiDAR waveform in its entirety (Jones and Vaughn 2010). The FW approach provides much greater information about the subject that has been scanned, however, FW also requires significantly greater energy requirements and data storage, particularly when used in large scale investigations (Jones and Vaughn 2010). The practical limitations of FW

LiDAR, amongst other considerations, contribute to the DR system being more frequently used for investigations at the landscape scale.

A limitation of DR LiDAR is that not all of the potential information during a scan is retained in the data capture process, wherein pre-defined laser returns (typically ranging 1-4 from a single pulse) are the points at which data is captured. The data created during the DR scanning process is a series of individual points which, when combined, create the point cloud. These data points are geo-located with XYZ coordinates, and other attributes including return number and waveform intensity (see Figure 1). As the DR data points only have a small footprint area relative to the operational height of the ALS, there are areas of the subject that are not scanned or get represented in the subsequent point cloud, even when the scan is at a very high resolution. Therefore supplementary analysis of the DR LiDAR data must be undertaken in order to gain greater insights about the condition of the subject.

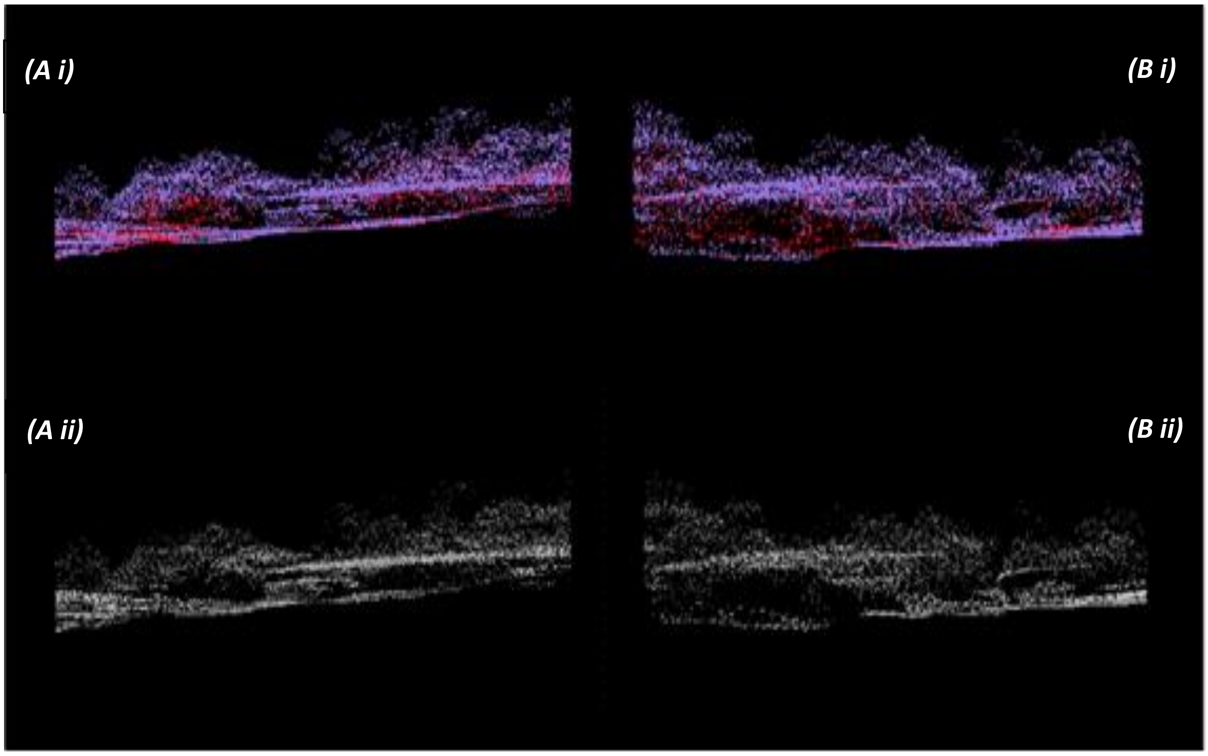

Figure 1 A visualisation of a discrete return (DR) light detection and ranging (LiDAR) point cloud of a woodland tree canopy. The images represent the same woodland area seen from both front view (A) and side view (B) perspectives. The image colouration shows the data classified by return number (i) and laser intensity (ii).

Previous research suggests that there is the potential to identify the structural attributes of individual tree canopies by using specific combinations of LiDAR metrics, thus enabling the classification of canopy structures (Falkowski, Evans et al. 2009). It has also been found that the structure of a standing tree and its interaction with other tree canopies around it presents a complex set of variables requiring correct identification to ensure that any subsequent canopy classification is undertaken accurately (Kato, Moskal et al. 2009). Accordingly for the purposes of this research, combinations of

LiDAR metrics will be investigated in order to ascertain what level of observations can be inferred about the subject tree canopies structures, following capture in a DR LiDAR point cloud.

Research Aim

The aim of this research is to investigate the potential significance of data relationships within a DR LiDAR point cloud of tree canopies and, which combinations of LiDAR metrics could be used to indicate where individual trees may have compromised structures with the potential for failure, in an attempt to improve tree risk assessment procedures.

Methodology

The LiDAR point cloud data was captured via an ALS, undertaken by NERC ARSF, over woodland in the north west of England. The woodland contains trees in a wide range of complex structural conditions and spatial arrangement. High levels of resolution were achieved in the DR LiDAR through incorporating a large percentage swath width overlap of approximately 50% on each flight line, which resulted in a high point density. Following ALS data capture, a series of random sample plots were geolocated and their physical boundaries established on the ground within the woodland area. The sample plots were representative of many different combinations of locally provenant tree species and lower vegetation communities, typically representing national vegetation classification W11 (*Quercus petraea – Betula pubescens – Oxalis acetosella* woodland). The woodland also contained areas of varying woodland management practices and canopy cover types ranging from individual, open grown trees (maidens) up to areas of total canopy closure (up to 100%). To aid the scope of the investigation, the sampling scheme included plots that were representative of varying percentile levels of canopy cover e.g. 10%, 20% etc. 26 sample plots measuring 20 x 20 meters were established and a range of individual tree measurement variables were taken using traditional woodland management and arboricultural techniques, to enable validation of the LiDAR data set.

Preliminary statistical analysis of the LiDAR data has been undertaken in order to identify the appropriate metrics that could be used to infer the structural condition of individual tree canopies. Primarily this has focussed on the significance of the laser return (r) as a potential indicator of structural condition (see Figure 2 and Figure 3). Subsequently a range of LiDAR metrics have been identified for further investigation, for example; average returns in the *n*th percentile, point cloud surface area measurement and the implication of data point clustering. Due to the early stages of this work, the investigation into the significance of these variables and identification of other relevant metrics is on-going.

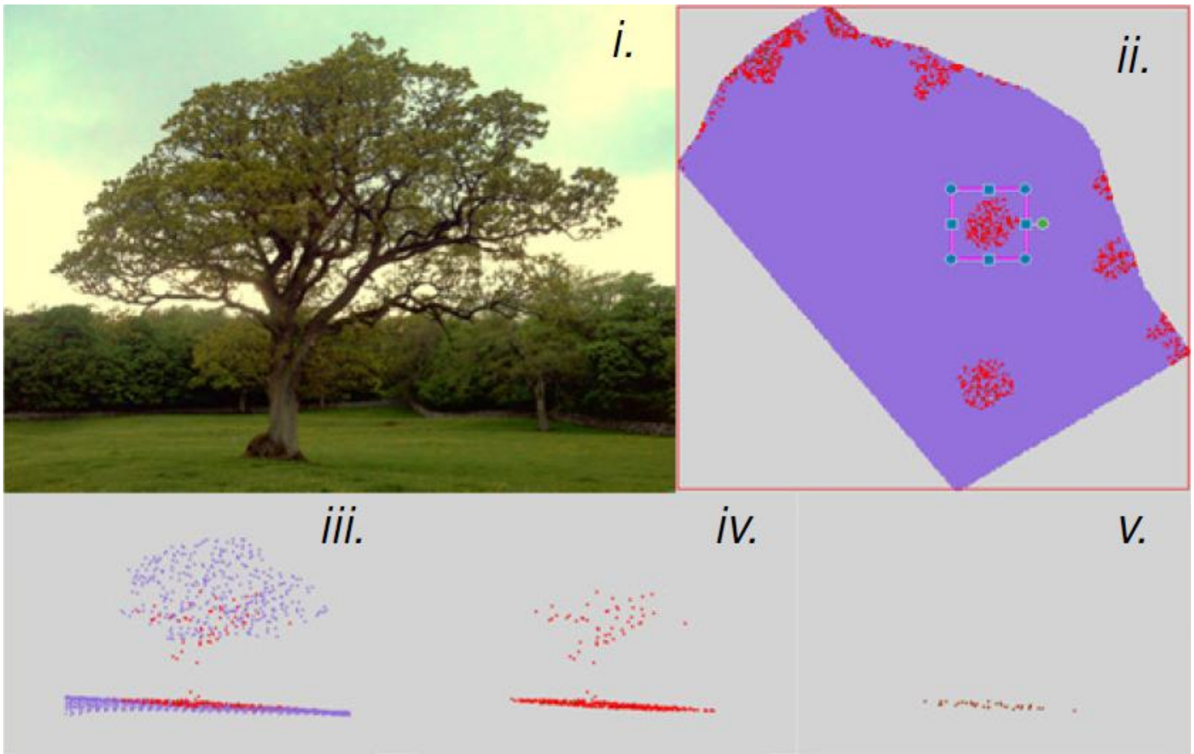

Figure 2 i. – A healthy control tree (Tree A). ii. – Tree A in the larger data set before extraction. iii. – Tree A's data point cloud showing 1st, 2nd and 3rd returns. iv. – 2nd and 3rd returns only. v. – 3rd returns only. Tree A has a well distributed, high number of 1st and 2nd returns from the canopy, and a high number of 3rd returns from the ground.

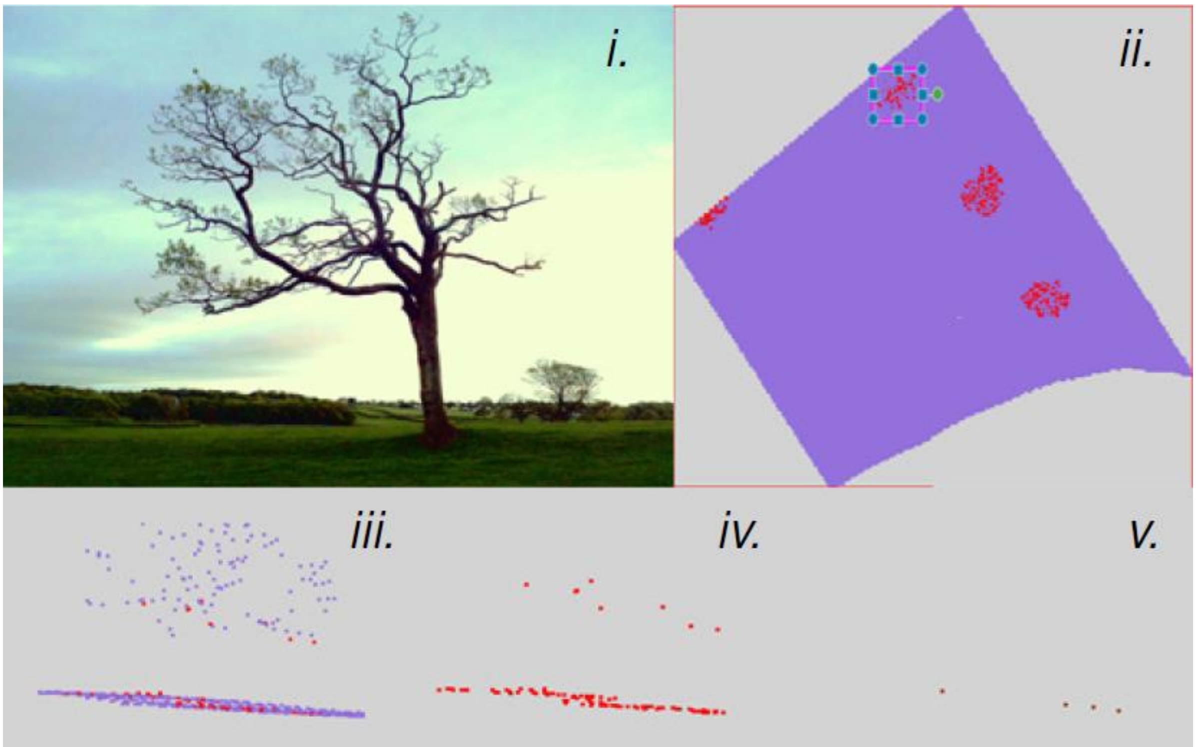

Figure 3 i. – A stressed or risk tree (Tree B). ii. – Tree B in the larger dataset before extraction. iii. – Tree B's data point cloud showing 1st, 2nd and 3rd returns. iv. – 2nd and 3rd returns only. v. – 3rd returns only. Tree B has only a moderate distribution and frequency of 1st returns from the canopy, and a low number of 2nd returns from the canopy with a low number of 3rd returns from the ground.

Results

Following analysis of 238 individual trees; early findings indicate that there are statistical relationships that can be used to infer particular structural characteristics. Through undertaking a MANOVA analysis, both standardized and unstandardized regression weights as discriminant function co-efficients are returned for each of the independent variables, r 1-4.

Table 1 *Standardized and raw discriminant function coefficients as unstandardized regression weights for LiDAR return (r) variables.*

Variable	Raw	Standardized
r1	-0.00429	-1.71796
r2	0.00780	1.64426
r3	-0.03895	-1.46073
r4	0.42858	0.81466

The positive trend, standardized value for r2 (1.64426), indicates that this variable has the greatest influence on the canonical variable as a discriminate function. Therefore the r2 values within the data are shown to have the greatest influence the independent variable, i.e. differences in structural condition. In order to satisfy that the statistical relationship between the dependant variable and the canonical variables is valid, a correlation was undertaken and is shown at Table 2

Table 2 *Correlations between the dependent (return number (r)) and canonical variables.*

Variable	Correlation
r1	0.87948
r2	0.74750
r3	0.68438
r4	0.34560

Table 2 shows that there is a positive correlation between the all of the return numbers and their canonical variable, with the combined r1-3 showing the greatest levels of correlation and r4, whilst still being positively correlated, exerts the least influence on observed condition. This suggests that from the observed analysis, r1-3 will be the most reliable data to be used in the development of metrics for the identification of the structural condition in trees, and that the frequency and distribution of r2 exerts the greatest influence.

Discussion and Conclusion

Following a review of similar research, it has been shown that creating a series of metrics, to aid the identification of structure types in trees is possible. At this early stage of investigation, only preparatory research and analysis has been carried out and there remains additional investigative work to be completed both in the field and laboratory. Early results suggest that there is notable influence of the 2nd return, r2, in indicating the structural condition of the subject trees. At this stage, it is envisaged that r2 will also have a prominent influence in deciding the validity of the metrics created during this investigation.

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Biographies

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