Using full-waveform lidar to characterise urban habitat structure and function

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Highlights: A novel method using terrestrial lidar to calibrate airborne lidar processing is presented. Attention is paid to the ability to detect understorey vegetation. Two deconvolution methods are compared and Gold's method was found to be superior. A variable noise threshold is needed to deal with weak signals and multiple scattering effects.

Key words: Waveform lidar, airborne, terrestrial, signal processing, urban vegetation.

Introduction

Urban areas are covering increasing areas of the world's surface and now contain over 50% of the global population. Increasing attention is being paid to the importance of urban wildlife and the impacts on urban greenspace on human wellbeing and provision of ecosystem services. There are well known relationships between urban greenness, the magnitude of the urban heat island, noise pollution and human-wildlife interactions. There is increasing evidence suggesting that interacting with wild animals improves human well-being [1] , and so there is a scientific driver towards understanding and quantifying greenspace connectivity for optimal town planning. Connectivity models predicting how animals move through a landscape can be used for this purpose, but currently there is little consensus on the best approach and little agreement about the types and scale of the input data needed [2].

A key determinant of connectivity is the three-dimensional distribution of vegetation structure and functional type. Airborne laser scanning (ALS) is the most appropriate tool for providing these data due to its ability to rapidly measure large areas accurately and non-destructively. This paper develops methods to measure the 3D structure of urban vegetation from ALS and discusses how they can be used to investigate urban habitat connectivity. Information on the full vertical canopy profile is important as different species inhabit different height bands. Terrestrial laser scanner (TLS) data were used as ground reference data to optimise the waveform signal processing method. Results were compared to the output of the ALS instrument manufacturer's (Leica) discrete return algorithm (captured in parallel to the full-waveform data) as this is a commonly used data type. Particular attention was paid to the capabilities of discrete return and waveform ALS data for describing understorey vegetation.

In order to extract vegetation structure from full-waveform ALS the signal must be denoised, calibrated to a physical intensity, system pulse shape effects removed, attenuation corrected for and then the signal strength converted to vegetation density at each point in the scene. This paper will demonstrate that process and show the results in the context of urban ecological greenspace mapping.

Field site and data

An urban area, including patches of woodland, buildings, parks and gardens in Luton, UK, was surveyed by the NERC-ARSF aeroplane in September 2012. Measurements were made with a Leica ALS50-II full-waveform lidar, Eagle and Hawk imaging spectrometers (covering the visible, near infra-red and short-wave infra-red wavelength regions) and a standard fixed format survey grade digital camera. The Leica ALS50-II is a 1064 nm lidar which records two streams of data, one using Leica's commercially confidential discrete return algorithm to output up to four points per laser shot and the other as full-waveforms sampled every 1 ns. The ground point density was between 0.25 m^{-2} and 5 m^{-2} depending on flight line overlap.

Eight ground plots were chosen to cover the full range of observed ALS waveform shapes. In August 2014 a Riegl VZ-400 TLS was used to collect between two and seven scans at each plot (depending on vegetation density) which were geolocated with the ALS data. An Ocean Optics USB2000 was used to collect ground, bark and leaf reflectance spectra within the plots.

Signal processing

A histogram of all ALS waveform bins was used to determine the background noise levels. This showed that noise was very stable (99% of values lay within 2 digital numbers of the mode), suggesting that it was due to a dark current rather than background illumination and could be removed by thresholding [3]. Previous work shows that simply summing all waveform bins above noise gives the most accurate measure of target reflectance for this type of lidar [4]. Returns from Luton airport runway were used to determine the system pulse shape and Gold's method [5] or Richardson-Lucy deconvolution [6] used to deconvolve the waveform, and the results of the two methods were compared. Both are iterative re-blurring algorithms for deconvolving the effect of system pulse blurring in the presence of noise. Gold's method is given by:

$$o^{(k+1)} = o^{(k)} \frac{i}{s \otimes o^{(k)}}$$

Where i is the original waveform, s the system pulse, $o^{(k)}$ the k^{th} estimate of the true signal and $\otimes$ the convolution operator. This is iterated over for either a fixed number of iterations (set to a maximum of 2,000) or until the change between consecutive estimates drops below a threshold (in the examples examined the result always converged). Richardson-Lucy deconvolution is very similar but with an extra blurring by the system pulse:

$$o^{(k+1)} = o^{(k)} \left(s \otimes \frac{i}{s \otimes o^{(k)}} \right)$$

This should make it more robust to noise but will take longer to converge and may not reach as sharp a result. These algorithms require several parameters to be set, such as the deconvolution tolerance, smoothing widths and noise threshold. These were tuned against "true waveforms" produced from the TLS data, representing the signal that the ALS would see without the noise and system pulse effects, but still including attenuation.

To produce these "true waveforms", the TLS data were voxelised [7] to the same size as the ALS waveform bins (15cm vertically and 30 cm horizontally) and a silhouette ray tracer [8], taking gap fraction within each voxel into account, was used to create the true waveforms. Non-linear optimisation was used to find the optimum signal processing parameters. The same TLS voxels (without ray tracing) were used as the 'true', reference vegetation profile in order to optimise the ALS attenuation correction and validate the results. Comparison between the raw ALS data (before any processing) and the TLS produced waveforms showed that the combination of using the beam divergence, hit intensity and gap fraction [8] accounted for attenuation, giving good estimates of the canopy up to the highest points within the plots. The accuracy at the canopy top reduced farther from the plot centre (notably falling off 15 m away), but the results within the central 10m were deemed accurate enough. Plots were split into separate optimisation and validation datasets.

Results

Gold's method was found to converge faster and give more accurate results than Richardson-Lucy deconvolution and so we use Gold's method here. It was not possible to set a fixed noise threshold that removed all subterranean noise and captured the understorey vegetation; either the threshold was too high to detect the weak signal from under dense canopies or else was so low that multiple scattering and electronic lag of the detector caused spurious subterranean hits. Therefore a variable noise threshold was needed, tuned to the background noise for each individual laser shot but also increasing through each waveform in order to avoid spurious returns from multiple scattering and electronic lag.

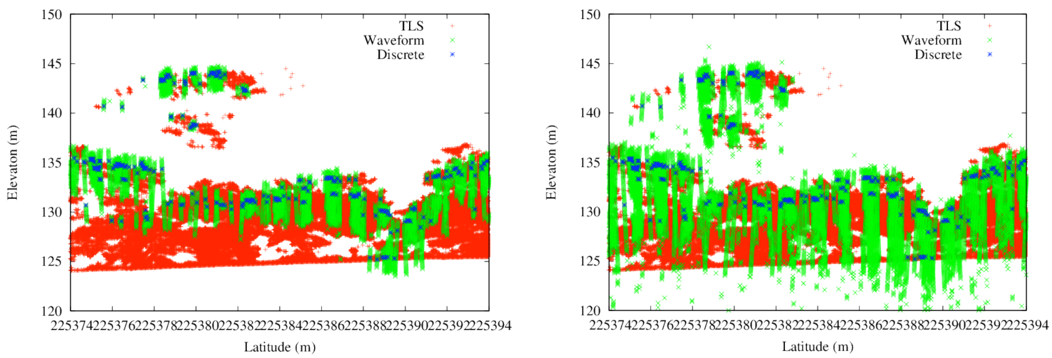

Figure 1: Comparison of TLS, ALS discrete and ALS waveform results with a high (left) and low (right) noise threshold.

Figure 1 shows that the discrete return algorithm gave no subterranean hits but did not give any returns from the understorey, suggesting that it used a high, conservative noise threshold. This would have been exacerbated by the discrete return dead time, of the order of 2 m. The discrete return algorithm will have been optimised for measuring the range to hard targets in order to produce accurate digital elevation models and so it is not surprising that it fails to characterise the complete vegetation canopy. In addition the discrete return data showed a bias in height of the order of an 80 cm underestimate.

Conclusions

It was found that Gold's method outperformed Richardson-Lucy deconvolution in terms of computational expense and RMSE of the retrieved vegetation profile relative to the TLS measurements. A fixed noise threshold was not suitable for all laser shots in a scene as it had to be set too high to measure weak returns from understorey in order to avoid multiple scattering and electronic lag effects. An adaptive noise threshold was required, changing between shots and along a waveform as multiple scattering becomes significant in dense canopies and may require more advanced denoising methods [10]. Further work using radiative transfer modelling will allow a thorough investigation and decoupling of these effects and work towards this using the librat ray tracer [9] is ongoing.

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