

Fourier transformation of waveform Lidar for species recognition

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In precision forestry, tree species identification is one of the critical variables of forest inventory. Lidar, specifically full-waveform Lidar, holds high promise in the ability to identify dominant hardwood tree species in forests. Raw waveform Lidar data contain more information than can be represented by a limited series of fitted peaks. Here we attempt to use this information with a simple transformation of the raw waveform data into the frequency domain using a fast Fourier transform. Some relationships are found among the influences of component frequencies across a given species. These relationships are exploited using a classification tree approach to separate three hardwood tree species native to the Pacific Northwest of the United States.

We are able to correctly classify 75% of the trees ($\hat{\kappa}$ 0.615) in our training data set. Each tree's species was predicted using a classification tree built from all the other training trees. Two of the species grow in proximity and grow to a similar form, making differentiation difficult. Across all the classification trees built during the analysis, a small group of frequencies is predominantly used as predictors to separate the species.

1. Introduction

Species identification is an important component of many forest surveys. Environmental quantifications of interest such as timber value and habitat quality highly depend on the species distribution within the stand. Because of this importance, techniques to quickly and accurately determine individual tree species or simply the proportion of a given species on a larger scale are intensively sought after. As it is more and more common for Lidar to be used for operational forestry, techniques to classify species from Lidar data are of great interest.

As the spatial structure of a tree is modelled quite well, it is tempting to believe that a Lidar data set of sufficient density might contain enough information needed to correctly distinguish several tree species from one another. Under this hypothesis, several authors have proposed methods of using discrete-point Lidar information (Holmgren and Persson 2004, Moffiet *et al.* 2005, Brandtberg 2007, Liang *et al.* 2007, Ørka *et al.* 2007, Kim *et al.* 2009). To improve upon these results, some have combined Lidar data with raster data sets in one form or another (Koukoulas and Blackburn 2005, Korpela *et al.* 2007, Holmgren *et al.* 2008, Säynäjoki *et al.* 2008). However, in such cases, the Lidar data are incorporated more to aid tree crown segmentation than for classification purposes.

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Recently, Lidar vendors have begun to make available waveform Lidar data sets. Waveform data sets contain an entire digitization of the intensity over a brief period for each light pulse. Mallet and Bretar (2009) provided a detailed introduction to such data and the instruments that collect these data. The potential to hold additional information about the target is likely increased along with the density of the recorded waveform data. Wagner *et al.* (2004) have argued that waveform data already contain sufficient information for target classification.

Each waveform contains information about the reflectivity, density and spatial arrangement of the leaves and branches of the target tree. Given the amount of information contained in a waveform, techniques that smooth this information, such as Gaussian decomposition, may risk losing important information. In its raw form, a waveform is a simple time series. Therefore, tools that have been used in the past to analyse time series may again prove their usefulness in this case. These tools allow for the transformation of the original data into forms that emphasize the temporal relationships between all the sample points. Such a representation of the data facilitates the search for patterns within the waveforms that may help distinguish a given tree species. In this article, we employ a technique commonly used in the analysis of time series, the Fourier transform, to distinguish three deciduous species native to large areas of the western United States with waveform Lidar data.

2. Methods

2.1 The study site

The Washington Park Arboretum in Seattle, Washington, is operated by the University of Washington Center for Urban Horticulture. The arboretum, which is approximately 230 acres (93 ha) in size, is planted with more than 10,000 catalogued woody plant specimens representing several genera. In addition much of the Arboretum contains natural stands of species native to Western Washington State, such as Douglas-fir (*Pseudotsuga menziesii* (Mirbel) Franco), western red cedar (*Thuja plicata* Donn ex D. Don), bigleaf maple (*Acer macrophyllum* Pursh), black cottonwood (*Populus balsamifera* L. ssp. *trichocarpa* (Torr. & A. Gray ex Hook.) Brayshaw) and red alder (*Alnus rubra* Bong.). The non-native trees in the arboretum are planted in groups by genus. Native species are also dispersed throughout the arboretum and can be found clustered in their own groups or sparsely mixed within the non-native trees.

2.2 Data processing

We applied the waveform data provided by Terrapoint USA Inc. (The Woodlands, TX, USA), who flew a RIEGL LMS-Q560 laser scanner, with waveform signal digitization, over the Washington Park Arboretum on 8 August 2007. This instrument was set to digitize waveforms at a sample interval of about 1 ns, or 15 cm in linear distance. Scan angle ranged from -30 to $+30$, and the pulse frequency was set at 133,000 Hz, resulting in a pulse density of about 10 pulses/m² (ppm) near nadir at ground level. For comparison, this would yield about 20 points/m² in a comparable first and last return discrete-point data set. A single 4.5-km looped pass in the North–South direction for the length of the arboretum, lasting about 6 min, provided nearly 49 million waveforms.

Within the same arboretum, Kim *et al.* (2009) geolocated and measured characteristics of the trees in 18 field plots within the Arboretum. The locations of these plots

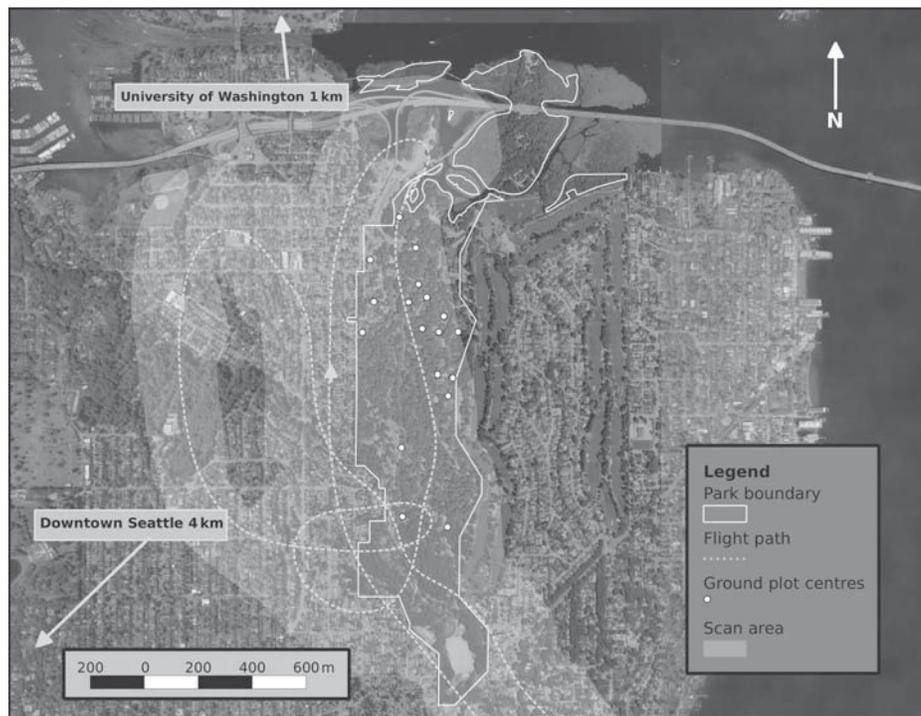


Figure 1. Map of the Washington Park Arboretum with flight path and ground plot locations.

are shown in figure 1. The field plots were installed systematically so that at least one plot is measured in each genus group of interest. Within each plot about 10–20 example trees were identified and measured during the summer of 2005. Typically, the measured trees were somewhat isolated, simplifying the process of crown delineation from the Lidar data. However, several groups of native species are arranged with densities similar to the densities of natural stands. Each of the trees measured in the field plots has been mapped into Universal Transverse Mercator (UTM) coordinates using an angle and distance from known points within the plots. These points were located with survey-grade global positioning system (GPS) units and these data were later differentially corrected for optimal accuracy.

To associate waveform data to individual trees on the ground, the tree crowns had to be delineated in mapping coordinates. Although it is possible to do this directly using a waveform Lidar data set, many tools already exist to perform such analysis on a discrete-point data set. We therefore used a discrete-point data set, built from the waveform data set, to create a raster image containing a digital canopy height model. In this model, the highest return elevation, above the digital elevation model (DEM), within each grid cell was stored. We used the method described by Hyypä *et al.* (2001a) to obtain an initial set of polygons representing the crown outlines of individual trees in the arboretum. This method works in an iterative manner: at each step neighbouring pixels are added to clusters surrounding local maxima of a filtered canopy height model. Under such an algorithm, many groups of trees are mistaken for single trees (Hyypä *et al.* 2001b). Although this should have little effect in the arboretum, the polygon for each tree in the training data set was visually inspected and, if necessary,

improved upon by hand. All waveforms with data inside the outline of each tree (at any height) were identified. Due to the large size of the full data set, this procedure was performed using code written in C programming language.

2.3 Fourier transform

In the analysis of time series, several tools are available to look for non-random patterns within the data. One technique is to look at the data in the ‘frequency domain’ to discover frequencies of strong influence. This is usually done with a discrete Fourier transform. This transform converts the original data into a set of coefficients representing the influence of sine and cosine waves of a known set of frequencies. Large coefficients are associated with heavy influence and imply that a higher amount of periodicity at the given interval is detected in the data. The transform loses no information, as the number of frequencies is equal to the number of samples in the original signal. Fast versions of the transformation exist under the name fast Fourier transform (FFT) and have a relatively low upper limit on computing time (Singleton 1979). The function ‘fft’ in the R programming language (R Development Core Team 2009) was used to compute the FFT on each waveform.

In this study, waveforms had 60 samples each, representing about 9 m of linear distance. Because of how the FFT works, only the coefficients of half of the frequencies are meaningful. With 60 samples, we can consider the amplitudes of the first 30 frequencies to be useful. For each tree, the averages (across all waveforms hitting a tree) for each of these 30 useful amplitudes were stored as variables named with a leading ‘M’ followed by the frequency identification number (M1–M30). Additionally, the standard deviations of each frequency were recorded as variables V1–V30.

Additionally, the average intensity value was kept for each waveform. This easily computed value represents the total amount of light reflected from each pulse. It is easy to see how this value might vary by species. The average and the standard deviation of these values for each tree were recorded as MI and VMI. In total, for each tree in the training data set, there are 62 variables that will be considered for use in classification as described in the next section.

The FFT algorithm assumes an equal time period between samples; however, in some cases the range values within each pulse data are not equally spaced. To greatly simplify the analysis, these facts were ignored, as a violation of this assumption is not too concerning in this case. The displacement of an occasional sample point should have little impact on the results. In most cases, the difference in intensity between two neighbouring samples is very small. We are also ignoring that our series is not of a periodic origin, as are our sinusoidal basis functions. It does little harm to pretend that our series repeats itself in both directions *ad infinitum*.

2.4 Classification

We attempted to correctly classify all trees in three hardwood species: red alder, black cottonwood and bigleaf maple. These species represent common hardwood species that grow naturally in the arboretum and, therefore, are represented well in the field data. To partition the data, we used a classification tree approach (Breiman *et al.* 1984, p. 18). The R library Tree contains a function of the same name for modelling with these classification trees (Venables and Ripley 2002, p. 266). Figure 2 shows the classification tree obtained by fitting the entire training data set. The variable and split

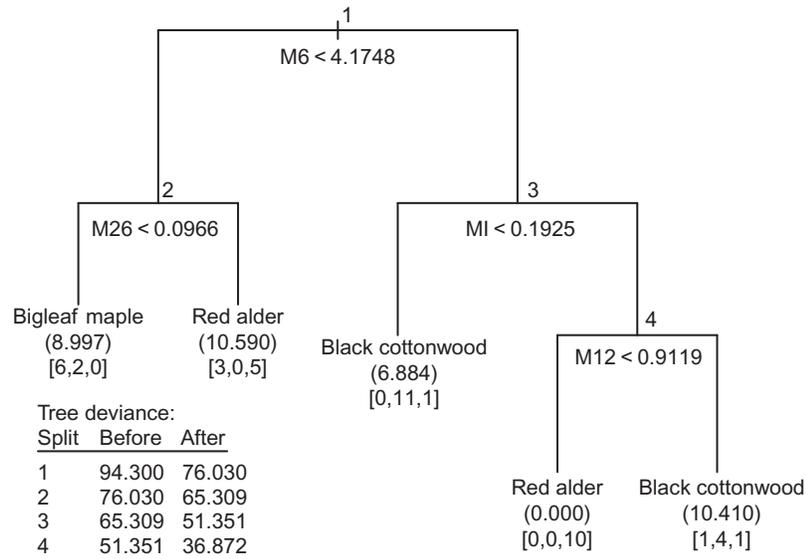


Figure 2. Example result of a classification tree fit to the training data. This is the tree returned when fitting to the entire training data set and pruning off one branch to simplify the structure. Above each split is the variable and level used to split the remaining trees into two subgroups. The reduction in tree deviance resulting from each split is shown in the bottom left. Leaf deviances are shown in parenthesis, actual class memberships in square brackets [bigleaf maple, black cottonwood, red alder].

value used is shown atop the fork. Each end node is labelled with the species most represented in the group of trees that have not been eliminated when traversing the tree from the root. Below each leaf the deviance within that leaf and the actual class membership are presented. The total tree deviance is the sum of the individual leaf deviances, and the reductions in the tree deviance as each split is added are shown in a table in the bottom-left corner of the figure.

With limited training data available, a leave-one-out cross-validation technique was used to estimate the actual predictive power of this technique when the trained model cannot be applied to a separate validation data set. The species of each tree was predicted by a classification tree that was trained with all other trees in the data. The numbers involved in such a process make refinement of each tree unpractical, and thus each tree was built from the built-in defaults of the tree function. In a non-academic application, the tree building could be better optimized and this may result in slight improvements in the classification accuracy.

3. Results and discussion

Table 1 shows the classification results from the cross-validation. The overall classification accuracy, or the portion of correctly classified trees, was 75%. The associated $\hat{\kappa}$ value was 0.615. For individual species, 70% of maples, 82% of cottonwoods and 71% of alders were correctly classified. Previous studies have accuracies ranging from about 64% (Brandtberg 2007) to around 95% (Holmgren and Persson 2004). However, the classification approaches and model applications vary quite drastically

Table 1. Results of the classification when each tree species is predicted from a classification model incorporating all other trees.

Species	Predicted			Producer accuracy (%)
	Bigleaf maple	Black cottonwood	Red alder	
Bigleaf maple	7	2	1	70
Black cottonwood	2	14	1	82
Red alder	1	4	12	71
User accuracy (%)	70	70	86	75

among these works. An indirect comparison of methods applied in different situations provides little information about the qualities of each. Although these results are not generally better than the previous results, they were obtained from a simple analysis with much room for improvement.

In the selection of species to classify, we left out all conifers. One reason for this omission is that it seems methods using discrete-point data are already capable of discriminating hardwoods from conifers. For instance, Reitberger *et al.* (2006) achieved 88% accuracy distinguishing conifers from hardwoods in a German mixed forest. Another reason for leaving out conifers is that the dominant shape of most conifers would mean that light pulses crossing the trees at steep angles would likely be drastically different than those passing at shallow angles. The more dome-like shape of most hardwoods might nullify this effect. It is possible that limiting analysis to more vertical scan angles could provide information to differentiate conifers from hardwoods or multiple species of conifers from one another. For this study we paid no attention to scan angle, and this is an area for improvement.

Table 2 lists all variables that were used in more than two classification trees out of the 44 built. The second column shows the frequency, in cycles per metre, associated with

Table 2. The most commonly used variables from the cross-validation procedure. Count is the number of cross-validation trees incorporating the variable. Those beginning with 'M' are means of the coefficients of a given frequency across all waveforms hitting a tree. Variables beginning with 'V' are variances. 'MI' and 'VMI' are the mean and variance of all intensity values for all waveforms hitting a tree, respectively.

Variable	Frequency (cycles/m)	Wavelength (m)	Count
M1	0.11	9.00	8
M6	0.67	1.50	37
M12	1.33	0.75	35
M17	1.88	0.53	4
M19	2.11	0.47	4
M21	2.33	0.43	7
M25	2.78	0.36	6
M26	2.89	0.35	36
V1	0.11	9.00	5
V8	0.89	1.13	3
V9	1.00	1.00	3
MI	–	–	37
VMI	–	–	4

the listed variables. However, the variables MI and VMI are not associated with any frequencies. The third column lists how many trees used the variables as a predictor variable.

The classification trees during the cross-validation procedure consistently relied on very few of the available variables. This is largely because in each cross-validation run, only one tree was replaced in the training data. However, it is still surprising that very few variables were so consistently included. The variables M6, M12, M26 and MI were included in a strong majority of the trees. Any biological meaning of these particular frequencies is not obvious, but there are some possible explanations for the importance of these frequencies. The frequency of M12 divided by M6 is 2.20 whereas M26 divided by M12 is 2.27. The fact that these two quotients are nearly the same may not be a coincidence. A sine wave of a given frequency is orthogonal to a sine wave of twice the frequency, assuming no phase shifts. Such a selection of variables may tend to be optimal due to this phenomenon. Of the three commonly used frequencies M6 represents a lower frequency, M12 a medium frequency and M26 a higher frequency. When compared with the dimensions of a tree, the wavelength of the lower frequency is on a scale that could represent between-branch variation whereas that of the higher frequency may represent within-branch variation.

The boxplots shown in figure 3 represent the range of each of the variables M6, M12, M26 and MI (panels (a), (b), (c) and (d), respectively) over all the waveforms hitting each tree. The species of each tree is represented by a shade of grey. There is a clear, observable difference between bigleaf maple and the other two species. Less clear is that the variables M12 and MI are more responsible for the differentiation of red alder and black cottonwood. Figure 2 shows that lower values of MI or high values of both MI and M12 lead to a decision of black cottonwood. This can be observed in the boxplots after prolonged examination.

This technique does show promise as an additional tool for the classification of tree species. There is sufficient information available in the raw waveform data to aid in the distinction of tree species. As in decomposition of waveforms into peaks, we have still managed to reduce the data. Instead of reducing waveforms to peaks, we have reduced a large amount of data into simple averages for each tree. One important note is that no spatial information, beyond that used to assign a waveform to a given tree, was used in this analysis. Related techniques incorporating the additional spatial information to look for patterns between waveforms might provide a large performance boost.

As waveform data are dense and very expensive when compared with discrete-point data, the next step is to test whether similar results can be produced from discrete-point data. Per-tree histograms of return abundance by height, such as those in Falkowski *et al.* (2009), appear similar to a single waveform. There may be some spatial patterns detectable in such 'waves' using the same Fourier transform.

It is important to note one potential drawback to using Lidar for individual tree results. As in discrete-point systems, the intensity values from waveform Lidar systems are dependent on time. This is due to an adaptive gain setting on the instrument changed dynamically during flight to adapt to large-scale changes in surface reflectivity. The intensity values over the length of the flight over the arboretum seem stable in this case. Effects of intensity scale changes on the results of this technique would likely depend on the degree of such change.

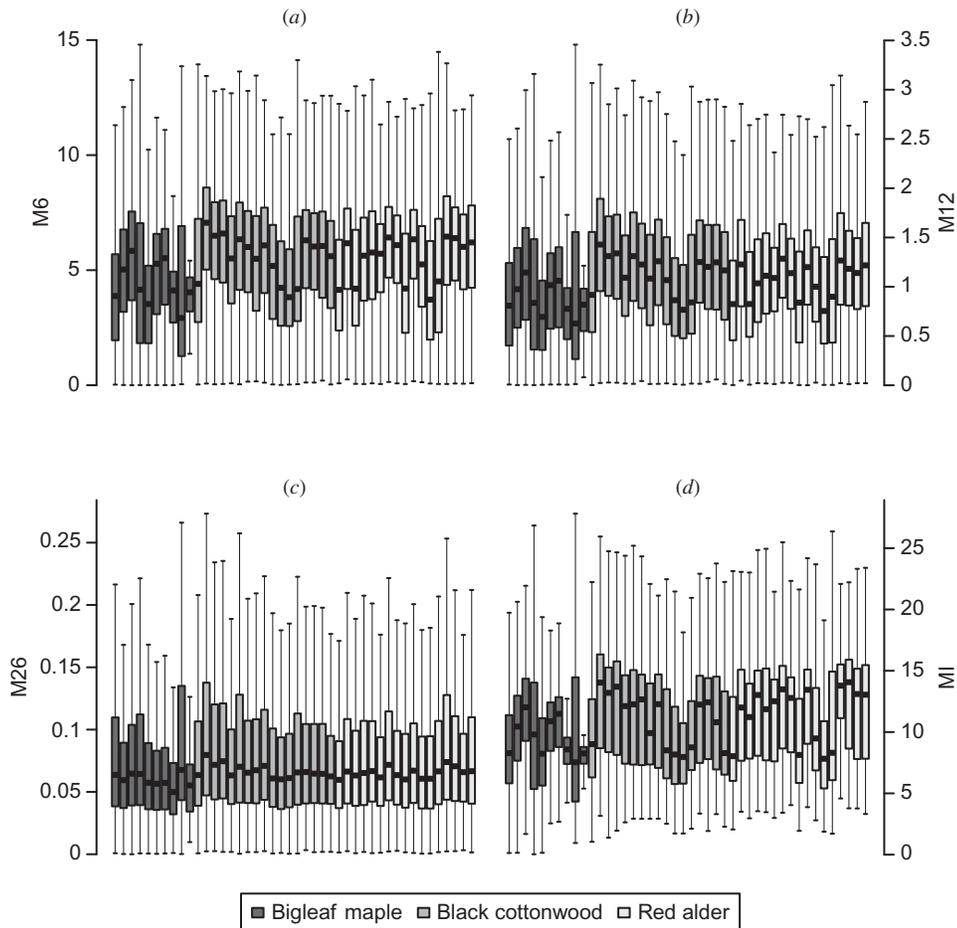


Figure 3. Boxplots of the values of four classification variables for all trees in the training data set. Each box represents one tree of the indicated species and represents all waveforms intercepting the tree's crown outline polygon (40–16,000 waveforms). The values of these variables have no units. Variables (a) M6, (b) M12, (c) M26 and (d) MI.

4. Conclusion

The technique described in this article provides an elegant method for the classification of tree species from waveform Lidar data. Further refinement, such as accounting for scan angle and more precise crown delineation techniques, could bring substantial increases in accuracy. This way of looking at the data in the frequency domain provides much information about branch and leaf arrangement patterns observed between waveforms. However, this viewframe provides little or no information about general tree shape and large-scale spatial arrangement, as do other methods using point data previously published (e.g. Holmgren *et al.* 2008, Kim *et al.* 2009). Therefore, these two ways of looking at the data may complement one another. This hypothesis needs to be tested through future research.

Although only three species were tested here, two are very similar, suggesting that the technique may perform well in regions with higher complexity. The use of Lidar

would also eliminate many complications imposed on optical imagery analysis by cloud cover in many regions. Because a waveform data set contains species information as well as the information contained in a discrete-point Lidar data set, it may soon be unnecessary to acquire an additional optically based raster data set for the sole purpose of species classification.

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References

- BRANDTBERG, T., 2007, Classifying individual tree species under leaf-off and leaf-on conditions using airborne lidar. *ISPRS Journal of Photogrammetry and Remote Sensing*, **61**, pp. 325–340.
- BREIMAN, L., FRIEDMAN, J.H., OLSHEN, R.A. and STONE, C.J., 1984, *Classification and Regression Trees, The Wadsworth Statistics/Probability Series* (Belmont, CA: Wadsworth, Inc.)
- FALKOWSKI, M., EVANS, J., MARTINUZZI, S., GESSLER, P. and HUDAK, A., 2009, Characterizing forest succession with lidar data: an evaluation for the Inland Northwest, USA. *Remote Sensing of Environment*, **113**, pp. 946–956.
- HOLMGREN, J. and PERSSON, Å., 2004, Identifying species of individual trees using airborne laser scanner. *Remote Sensing of Environment*, **90**, pp. 415–423.
- HOLMGREN, J., PERSSON, Å. and SÖDERMAN, U., 2008, Species identification of individual trees by combining high resolution LiDAR data with multi-spectral images. *International Journal of Remote Sensing*, **29**, pp. 1537–1552.
- HYYPÄ, J., KELLE, O., LEHIKONEN, M. and INKINEN, M., 2001a, A segmentation-based method to retrieve stem volume estimates from 3-d tree height models produced by laser scanners. *IEEE Transactions on Geoscience and Remote Sensing*, **39**, pp. 969–975.
- HYYPÄ, J., SCHARDT, M., HAGGRÉN, H., KOCH, B., LOHR, U., PAANANEN, R., SCHERRER, H., LUUKKONEN, H., ZIEGLER, M., HYYPÄ, H., PYYSALO, U., FRIEDLÄNDER, H., UUTTERA, J., WAGNER, S., INKINEN, M., WIMMER, A., KUKKO, A., AHOKAS, E. and KARJALAINEN, M., 2001b, HIGH-SCAN: the first European-wide attempt to derive single-tree information from laserscanner data. *The Photogrammetric Journal of Finland*, **17**, pp. 58–68.
- KIM, S., MCGAUGHEY, R., ANDERSEN, H. and SCHREUDER, G., 2009, Tree species differentiation using intensity data derived from leaf-on and leaf-off airborne laser scanner data. *Remote Sensing of Environment*, **13**, pp. 1575–1586.
- KORPELA, I., DAHLIN, B., SCHÄFER, H., BRUUN, E., HAAPANIEMI, F., HONKASALO, J., ILVESNIEMI, S., KUUTTI, V., LINKOSALMI, M., MUSTONEN, J., M., S., SUOMI, O. and VIRTANEN, H., 2007, Single-tree forest inventory using lidar and aerial images for 3D treetop positioning, species recognition, height and crown width estimation. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, **36**, pp. 227–233.
- KOUKOULAS, S. and BLACKBURN, G., 2005, Mapping individual tree location, height and species in broadleaved deciduous forest using airborne LIDAR and multi-spectral remotely sensed data. *International Journal of Remote Sensing*, **26**, pp. 431–455.
- LIANG, X., HYYPÄ, J. and MATIKAINEN, L., 2007, Deciduous-coniferous tree classification using difference between first and last pulse laser signatures. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, **36**, pp. 253–257.

- MALLET, C. and BRETAR, F., 2009, Full-waveform topographic lidar: state-of-the-art. *ISPRS Journal of Photogrammetry and Remote Sensing*, **64**, pp. 1–16.
- MOFFIET, T., MENGERSEN, K., WITTE, C., KING, R. and DENHAM, R., 2005, Airborne laser scanning: exploratory data analysis indicates potential variables for classification of individual trees or forest stands according to species. *ISPRS Journal of Photogrammetry and Remote Sensing*, **59**, pp. 289–309.
- ØRKA, H., NÆSSET, E. and BOLLANDSÅS, O.M., 2007, Utilizing airborne laser intensity for tree species classification. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, **36**, pp. 300–304.
- R DEVELOPMENT CORE TEAM, 2009, *R: A Language and Environment for Statistical Computing* (Vienna, Austria: R Foundation for Statistical Computing).
- REITBERGER, J., KRZYSZEK, P. and STILLA, U., 2006, Analysis of full waveform LiDAR data for tree species classification. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, **36**, pp. 228–233.
- SÄYNÄJOKI, R., PACKALÉN, P., MALTAMO, M., VEHMAS, M. and EERIKÄINEN, K., 2008, Detection of aspens using high resolution aerial laser scanning data and digital aerial images. *Sensors*, **8**, pp. 5037–5054.
- SINGLETON, R.C., 1979, Mixed radix fast fourier transforms. In *Programs for Digital Signal Processing*, I.D.S.P. Committee (Ed.) (Piscataway, NJ: IEEE Press).
- VENABLES, W.N. and RIPLEY, B.D., 2002, *Modern Applied Statistics with S* (Berlin, Germany: Springer).
- WAGNER, W., ULLRICH, A., MELZER, T., BRIESE, C. and KRAUS, K., 2004, From single-pulse to full-waveform airborne laser scanners: potential and practical challenge. *International Archives of Photogrammetry and Remote Sensing*, **35**, pp. 201–206.