

WAVEFORM FEATURES FOR TREE IDENTIFICATION

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ABSTRACT:

Interest in full-waveform airborne laser scanning (ALS) data has significantly increased with the release of waveform digitizers by commercial vendors. Despite the recent widespread availability of full-waveform data, the full potential of this type of data has yet to be realised. Some of the most promising applications for waveform data can be found in various fields of forestry, in which ALS data can aid in understanding single-tree characteristics. Waveform data can provide both vertical and horizontal information on forests. In this article, we study the feasibility of using full waveform data for tree identification. This study also considers the applicability of methods designed for use with conventional data, the possibility of generating methods that could use considerably denser point clouds extracted from full-waveforms, as well as the applicability of single descriptive or distinct waveform characteristics for tree species classification and tree parameter extraction. In addition, waveform data is compared with terrestrial close-range images. Superimposing waveform data on registered close-range images offers an excellent opportunity for understanding the waveform in greater detail.

1. INTRODUCTION

Airborne laser scanning (ALS) has become a commercially accepted tool for modelling our environment. For the past decade, the majority of commercial applications have concentrated on using the last and first pulses. Recently, ALS vendors have expanded the provided number of returns, thereby enabling users to more easily gain information between the first and last pulses. Typically, between two to five returns have been employed, though some ALS systems can register the full-waveform.

The methods and problems of interpreting recorded waveforms have recently been studied by Hofton et al. (2000) and Wagner et al. (2006). Current methods for waveform processing focus on using a Gaussian decomposition of the signal to derive individual echoes, derived from the main scatterers in the path of the laser beam (Wagner et al., 2006; Reitberger et al., 2006a).

ALS data has become popular for estimating forest parameters. The two main feature extraction approaches for deriving forest information from ALS point clouds have been based on statistical canopy height distribution (e.g., Næsset 1997) and individual tree detection (e.g., Hyypä and Inkinen, 1999; Persson et al., 2002). Distribution-based techniques typically use regression, non-parametric or discriminant analysis for forest parameter estimation. Individual-tree-based approaches use the neighbourhood information of canopy height point clouds and the pixels of CHMs for extracting such features as crown size, as well as individual tree height and location. Finally, forest inventory data are estimated using existing models and statistical techniques.

Before current commercial small-footprint waveform digitizers became available, some forest parameters were statistically

extracted using large-footprint waveform laser altimeters such as "Scanning Lidar Imager of Canopies by based on Echo Recovery" (SLICER) and "Laser Vegetation Imaging Sensor" (LVIS) (Ni-Meister et al. 2001, Harding et al. 2001).

Tree species is an essential index in forest studies, inventories, managements and other forest applications. Pyysalo and Hyypä (2002) investigated a method for describing the tree shape by its 3D point cloud density distribution in both height and width dimension (Reitberger, 2006a). Holmgren and Persson (2004) showed that pine and spruce can be separated with 95% accuracy using laser scanner data. Knowledge of the echo type (first, last, only) together with elevation information was used to extract features from tree crowns. In Brantberg (2007), a digraph process was used for tree species classification, and the shape characteristics of a marginal height distribution were used to improve the tree height estimate. The potential use of waveform data for tree species classification has been presented, e.g., in Reitberger et al. (2006b).

If a size-independent representation of the point cloud structure can be formed, the corresponding features can be represented using primary components or other data compression methods. Waveform-induced point cloud densification could enable the generation of structural features that are detailed enough to allow for species classification.

In this article, we present various experiments on tree identification using waveform laser data. Two types of methods are used: methods based on single descriptive or distinct waveform characteristics and those that use considerably denser point clouds extracted from the full-waveforms. In addition, we also present the integration of ALS waveform echoes with terrestrial close-range images.

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2. DATA

2.1 Waveform Data from Espoonlahti

The study data are from the Espoonlahti area and were recorded August 31st 2006 with a TopEye MKII Palmer scanner. A flying altitude of 300m was used, with the scan angle varying between 9 and 25 degrees, as measured from the scanner position to the recorded point position. The waveform sample interval was 1 ns, corresponding to approximately a 15-cm resolution in the beam direction. The pulse length was 5 ns. The footprint of a single laser beam on the ground was approximately 30 cm caused by a beam divergence of 1 mrad. The mean point density was 16.6 points/m².

2.2 Reference Lidar Data

As a reference, we use the automatically extracted points from the TopEye MKII system, which produces first and last pulse data. For comparison of structural features, we also used the data from Optech ALTM3100 flight on July 12th 2005 with combined point cloud from 1000 and 400 m flying heights. Fig. 1 presents the point distributions of the systems used in the case of a birch.

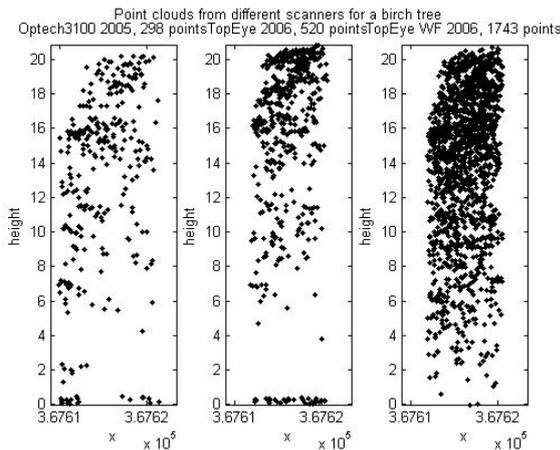


Figure 1. Birch tree example of point distribution for the data types used.

2.3 Photographs

Close-range images were captured using a Nikon D100 camera with a Nikkor 24-85 mm lens. The size of the CCD array was 3,008 x 2,000 pixels. A zoom setting of 24 mm was used during the image capture. The camera was calibrated in the test field at the Helsinki University of Technology (TKK). The original images were resampled in order to eliminate the effect of lens distortions.

3. EXPERIENCES WITH WAVEFORM METHODS FOR TREE SPECIES IDENTIFICATION AND FINDING TRUNK LOCATIONS

3.1 Methods Based on Points Extracted from Waveform

3.1.1 Tree Top Shape Identification

It is more convenient to detect and locate treetops rather than crowns, especially when occurring in clusters. Certain species have distinctive top shape; for example, the spruce usually

shows a cone-shape crown with a small open angle. Ideally, the shape of the crown can be modeled in 3D space by surface fitting (e.g., Holmgren and Persson, 2004). In our study, the crown top was explored in vertical projection and described with 2D curve parameters. At first, the crown points were projected onto four vertical planes through the assumed trunk position, in cardinal and half-cardinal directions. The final projection was constructed as a superposition of these four planes, which roughly expressed the convex hull of the crown. In the description phase, top shape was described by discharging all inner points and fitting a parabola based on the points lying in the topmost two meters.

Fig. 2(a) and Fig. 2(b) plot fitted curves in North-South projection for typical pine and spruce; Fig. 2(c) and Fig. 2(d) show the curves for 8 pine and 8 spruce trees, respectively. In general, the open angle for spruce is smaller than that for pine, thus providing a likely indicator for species identification.

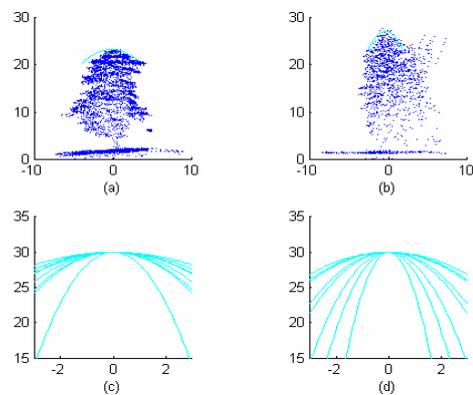


Figure 2. Tree top shape identification. (a) Pine with fitted curve, (b) spruce with fitted curve, (c) curves of eight pines and (d) curves of eight spruces. For comparison, curves were plotted at the same vertex in (c) and (d).

Mean increase WF/system %	Crown top points	Points used in tree top algorithm
Spruce	139%	115%
Pine	132%	106%

Table 1. The second column describes the mean points increase in the tree crown top, comparing the available points extracted from the waveform with points from first/last pulses. The third column presents the points increase in the treetop shape identification algorithm.

Table 1 shows that the points extracted from the waveform located inside the canopy are of little practical use, when employing shape predicting methods developed for first and last pulse data. The result is only indicative due to the small sample size. Verifying this result would require more data from different species and other environments.

3.1.2 Vertical and Horizontal Density Features

First and last pulse and waveform densified data are studied to determine those features that both represent the characteristic tree shape of different species and are independent of tree size. In our examples, the height of each tree is divided into ten

equal-sized bins. As a height feature, we use the percentage of points falling into each height bin.

Fig. 3 plots the height features of eight trees for each of the four tree species. It can be seen that the feature describing the height of a pine has the greatest point density near ground level. In contrast, the deciduous trees, birch and willow, have a maximum density in the upper canopy. The spruce tree has the most uniform point distribution along height bins. These height features only consider the point cloud distribution in the vertical direction. As structural features, we use both height and distance from the assumed trunk position. For simplicity, the location of the highest laser point is assumed to be trunk position. If the treetop is clearly asymmetrical, the centre of the point cloud is used. The point cloud is divided into ten height bins and five distance bins. The distance bins are cylindrical volumes around the trunk. Thus, distance bins located far from the trunk have larger sample percentages than would the inner distance bins. Different grey levels of the structural feature matrix elements in Fig. 4 describe the percentage of all the points falling into single height-width bin.

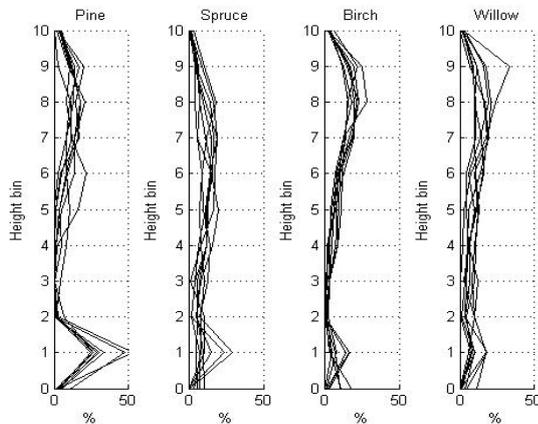


Figure 3. Eight representatives from each of four species are plotted to visualize the stability of the height feature in dense point clouds.

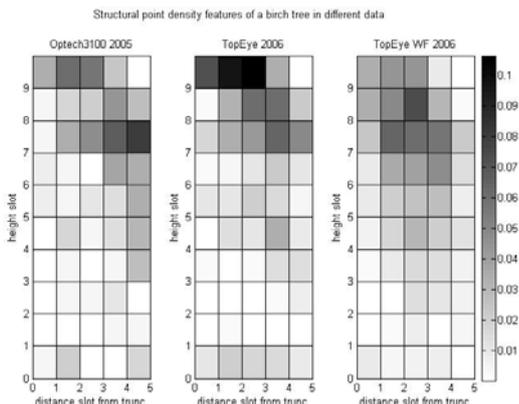


Figure 4. Structural density representations of the birch tree created from the point cloud in Fig. 1. The darker the structural element, the more points are located in the corresponding volume.

The advantage of using structural or height features to represent trees is that trees of different physical dimensions and point cloud size can be compared and dimension reduction methods can be used to enhance the computation.

The usability of height and structural features for species classification was tested using a sample of 32 trees, 8 samples from each of four species: pine, spruce, birch and willow (*Salix Siberica*). In the tests, the Euclidean distance between feature vectors was used as the distance metric. The leave-one-out method was employed for classifying each tree to one of the four species; for each tree in turn, the species information of other trees is used for determining the species of the current tree. In a nearest neighbour test, the distance to the feature vectors of 31 other tree samples was calculated, and each tree was classified to the same species as the closest neighbour. In the centre distance test, we computed the mean feature vectors for each species. Each tree was classified to the species whose feature centre was closest to the tree feature.

Height:	pine	spruce	birch	willow	Total
Dense 1-nn	75%	13%	75%	0%	41%
Thin 1-nn	88%	25%	75%	0%	47%
Dense cd	88%	75%	88%	25%	69%
Thin cd	100%	13%	63%	13%	47%
Structural:	pine	spruce	birch	willow	Total
Dense 1-nn	50%	63%	88%	63%	66%
Thin 1-nn	88%	75%	88%	75%	81%
Dense cd	50%	50%	88%	75%	66%
Thin cd	100%	13%	63%	75%	63%

Table 2. For each species, the percentage of correctly classified trees for waveform densified (Dense) and first and last pulse (Thin) TopEye data in nearest neighbour (1-nn) and centre distance (cd) methods.

In Table 2, two different distance metrics have been used to study whether the densified point cloud improves the separation between feature vectors of different tree species using height and structural features. The nearest neighbour method is likely to suffer from outlier samples. In larger samples, the nearest neighbour method should be k-nn, with a k variable of at least three. This result is only suggestive due to the small sample size. In a more realistic scheme, the sample centres would be calculated using a small training sample from each of the species.

Recently, Reitberger (2006a) compared the number of TopEye System points and waveform-extracted points. The increase in points for leaves on deciduous areas was 123%, but 230% for coniferous trees. For our sample, the respective values are 376% (Birch, Willow, leaf on) and 254% (Pine, Spruce). The difference in the percentages above is probably due to different area determination around the tree. We have not yet found an explanation for the fact that Reitberger et al. (2006) found a larger increase in the points for coniferous trees, whereas our study found a higher increase for deciduous ones.

3.2 Methods Using Single Waveform Features

In this section, we consider the possibility of examining the individual waveforms hitting a single tree. Such waveforms could be used to find information on tree trunk location or tree species. The use of the features extracted from the waveform is considered in Wagner et al. (2006), in which the authors studied the range, amplitude, pulse width and backscatter cross section information for target discrimination.

Fig. 5 describes the number of details in the waveform data. The left graph plots the points extracted from waveforms,

hitting the manually delineated tree canopy. Because of the relatively large scan angle, the extracted points occupy a much larger area than the original point cloud. This is of particular concern when analysing a dense forest. In the middle plot, only those waveforms are selected that travel across the point cloud centre. The right plot shows a densely sampled plane that slices the canopy when consecutively sent pulse waveforms are used together. In order to use features to measure characteristics such as trunk hits, it is essential that these features can be found computationally efficiently from large waveform data sets.

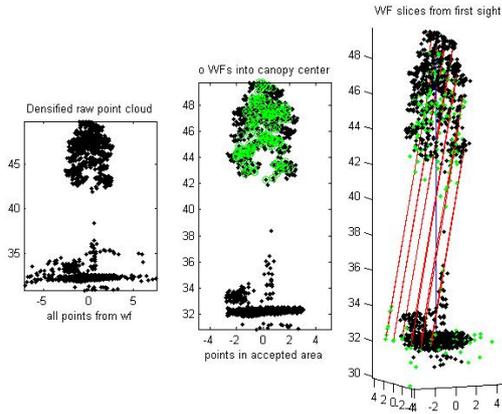


Figure 5. The left image shows all of the extracted points. In the middle image, the points with waveform directed into the tree canopy are plotted in green. The right image visualises a single slice from the consecutive waveforms.

3.2.1 Distinctive waveform profiles

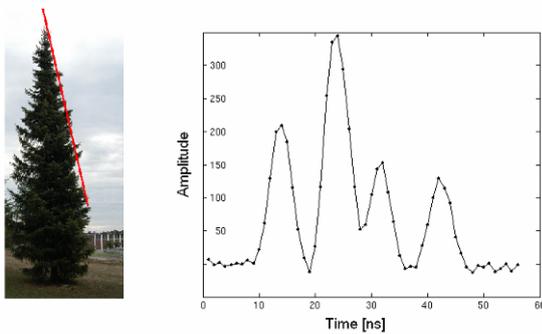


Figure 6. A multi-peaked waveform profile (right) is characteristic for signals that hit the spruce at a certain angle (left).

A laser beam that passes through spruce at a certain angle produces a multi-peaked waveform profile, as shown in Fig. 6. The return signal, composed of reflections from branch peaks and waveform amplitude, varies strongly as the signal passes through the foliage. To automatically determine multi-peaked waveforms, we developed an algorithm based on the divergence of signal amplitudes. The divergence was calculated from the part of the signal that originated from the tree crown, taking into account the fact that divergence was found throughout that part of the signal. Using this algorithm, we found several multi-peaked waveforms among each studied spruce. These waveforms were also found among pine data, though not as often as was the case with the spruce samples. Spruce can be identified based on the assumption that they cause more multi-

peaked waveforms than do pines. In this study, 0-50 % more multi-peaked waveforms were found from the spruce data compared to the pine data, though the results depend on algorithm parameters and several other factors. At the moment, only a few trees have been analyzed and more waveform data is needed to gain statistically reliable results.

3.2.2 Trunk echoes

Typically, two strong echoes were found in the case when the signal first hit the tree foliage and then the trunk, as seen in Fig. 7. Based on this information, an algorithm was developed to find tree trunk waveforms. The algorithm uses waveform data originating from the upper part of trees and restricts the distances between strong echoes. This was important to avoid confusion with signals of similar appearance originating from foliage and the ground. Several trunk waveforms were found from each spruce and pine, most of which seem to suggest roughly the same trunk location, thus allowing divergent points to be filtered out and the trunk position to be determined. In the future, field survey data are required to detect absolute errors arising from the determined trunk points.

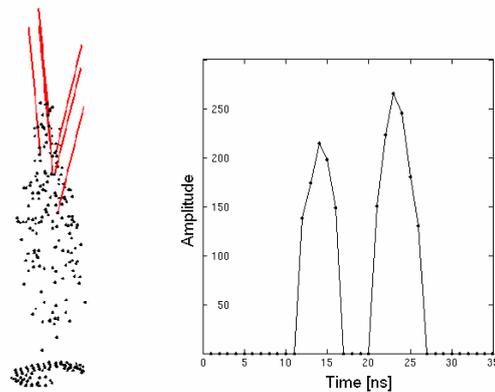


Figure 7. The spruce point cloud and waveform signals that hit the tree trunk (left). The waveform profile on the right is typical for signals that hit both the foliage and the trunk.

3.3 Integration of the ALS Waveforms with Terrestrial Close-Range Images

Registered close-range images are the most illustrative references when trying to understand the behaviour of the ALS. Unlike images derived with ALS, the internal geometry of the images is well known. In addition, the further perspective gained from terrestrial close-range images adds supplementary information to the laser scanning data. Such a comparison can reveal, for example, the effect of weather conditions.

During the test flight in Espoonlahti, the wind was relatively strong. The effect of the wind is clearly visible when the ALS data was superimposed onto the example images (Fig. 8). The registration of the images and ALS was completed using the interactive orientation method (Rönholm et al., 2003). For registration, the most stable features were observed, such as house roof, antennas, chimneys, pipes, and lamps. Unfortunately, movement of the treetop prevented sensible stereo viewing of the canopy, as the location and the shape of the treetop differed slightly in all images as well as in the ALS data. Fig. 8 shows how the tree canopy of the pine in the laser data does not fit perfectly with either of the two registered

images. Nevertheless, the laser point cloud fits very well with the roof of the building.

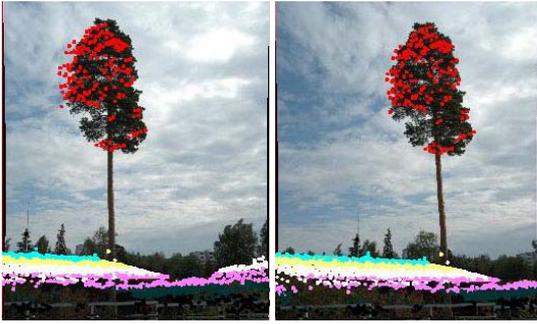


Figure 8. The first pulses are superimposed onto two registered terrestrial images. The colour coding is chosen to visualise the heights of the point cloud. The effect of the wind is clearly visible – the canopy of the tree has moved between the capture of the first and second images.

The full-waveform ALS data can be visualised by superimposing the echo rays onto the images. In Fig. 9, the ALS data is superimposed in two convergent images that are captured at an almost 90-degree angle to each other. The chosen camera locations and viewing directions make it easier to perceive the 3D shape and the behaviour of ALS data. If the canopy had been more stable, the stereo views from these two viewing directions would have been even more informative. For visualisation of the waveform data in Fig 9, we calculated the 3D location of each intensity value along the waveform echoes. The smallest intensity values were considered noise and thus rejected. The brightness of the colour describes the measured intensity values.

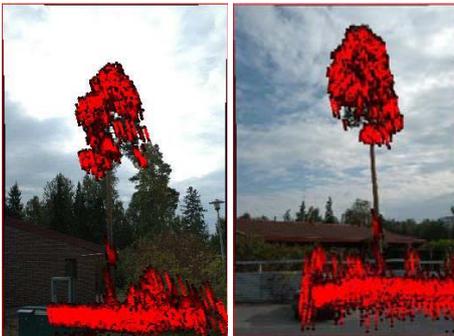


Figure 9. The full-waveform superimposed onto images. The difference in the viewing angles of the images is close to 90 degrees.

The superimposed ALS data is very informative. For example, the echoes that have hit the trunk can be selected using images (Fig. 10). Perpendicular image capturing can aid in this purpose. First, the area around the trunk is selected from the first image. The result is a cross-section of the echoes that can then be superimposed onto the next image. The different perspective of the second image visualises the cross-section from the side. Second, the area around the trunk is now selected from this second image. The intersection between these two cross-sections includes potential echoes that have hit the trunk.

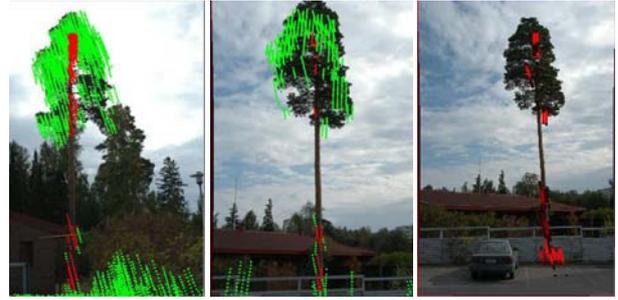


Figure 10. Using images for finding the trunk of the tree from the waveform data. The intersection of two perpendicular cross-sections finds potential echoes that have hit the trunk.

Although the total number of echoes that have hit the trunk is small, the waveform data includes significantly more information about the trunk than that provided by the first pulses alone. The first pulses have succeeded in detecting the trunk only in the lowest part of the tree and the number of hits is less than half of the number of trunk hits in the waveform data. Figs. 11 and 12 present some examples in which the information concerning the trunk is not located in the first pulse.

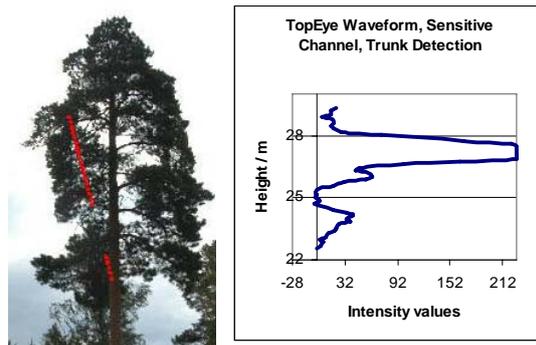


Figure 11. Waveform echo passes through the thick upper foliage before reaching the trunk. The echo is denoted in the image by uniform colour in order to enhance visibility of small intensity values.

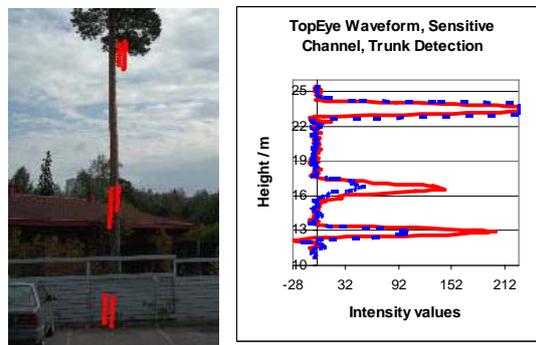


Figure 12. Two similar waveform echoes pass through thin branches of the upper foliage, detecting the trunk and continuing to the ground. The echoes are denoted in the image by uniform colour in order to enhance visibility of small intensity values.

4. CONCLUSIONS

Full-waveform data have great potential for improving the classification of tree species. The waveform can be used for densifying tree point clouds for more detailed information on tree structure. The benefit of densification is likely to be moderate for algorithms that use the special characteristics of the first and last pulse data, as described in section 3.1.1. However, those features based on density are likely to benefit more, since the large amount of data suppresses the effect of outlier points, different scan patterns and differences in the sampling resolutions. Table 2 presents preliminary classification results for height and structural features. The results show reasonable separation between the tree features of different species, despite the small size of the test sample. With larger data sets, we expect to gain more reliable estimates of the feature distribution for each species.

Single descriptive waveforms, studied in section 3.2, present a different approach for tree classification: instead of solving compute-intensive statistical densities, our method searches for simple descriptors of each species. Such waveforms could be used, for example, in decision-tree-based classification systems. In addition, this method enables detection of tree properties such as precise trunk position to be determined. To find the most informative single waveform types, a detailed knowledge is needed of the different types of waveforms and the typical locations in which they may occur.

Full-waveform data can be superimposed onto registered close-range images in order to obtain detailed information on the behaviour of the data. Visually, it is easy to find interesting waveforms if their nature can be verified from images. These waveforms can be chosen and examined separately. Stereo images would provide an easy interface for visualising waveform data. Unfortunately, windy conditions may cause instability of the tree canopies, thereby preventing sensible stereo examination, especially when images are not captured simultaneously. Alternatively, images can be taken convergently from different sides of a target. However, such convergent image acquisition would not allow stereo viewing, though it also provides a good impression of how light rays are located in the 3D space.

The usefulness of the superimposed ALS data is based on the human ability to find correspondences and similarities between images. It is very difficult to understand the true behaviour of ALS data if it cannot be compared with real images. Terrestrial close-range images give detailed reference data, and the viewing perspective which differs from that offered by ALS data gives additional information concerning the targets. A fuller understanding of these waveforms should make it possible in the future to develop improved tools for interpreting and classifying full waveform data.

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