Extraction of vegetation for topographic mapping from full-waveform airborne laser scanning data

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Abstract

Most of the research using lidar on vegetation has focussed on deriving forest and single tree characteristics. Very few studies have looked at mapping vegetation, including low vegetation, for topographical mapping. The aim of this study was to evaluate the classification and extraction of vegetation characteristics for topographic mapping using full-waveform airborne laser scanning data. The laser data were captured at a height of approximately 950m above ground level providing a point density ranging from 0.5-0.8 points per m^2. A subset of points representing the various surfaces – vegetation, roads and buildings – was extracted and analysed to identify surface attributes to be used for further analysis and classification. Vegetation was classified into three categories based on height from the ground. The training dataset comprised approximately 16000 points selected from one million data points. A Triangulated Irregular Network (TIN) was created from the elevation of the points. Classification was undertaken on the point cloud based on the local statistical variation of attributes of TIN triangles as well as attributes of the individual points. We show that a decision-tree classifier performs significantly better than k-means clustering based on the train-all-test-all accuracy. Future work will establish the accuracy of the classification of vegetation objects on untrained data.

Keywords: Full-waveform Lidar, Vegetation, Mapping, Classification

1. Introduction

The measurement of distances using laser scanning (Lidar), is fast becoming a standard tool in the fields of remote sensing, surveying and mapping. Laser scanning can provide accurate and fast digital models of the topography, and vertical structures of target surfaces at much lower field-operation costs point-for-point, with reduced post-processing time and effort compared to traditional survey methods. There are two distinct techniques used in lidar systems based on how the return signal is recorded. The more commonly used discrete return lidar systems record single or multiple return signals for every emitted pulse. The other emerging technique is waveform-digitizing lidar which samples and records the full waveform of the return signal to capture a complete elevation profile within the target footprint, or the area illuminated by the laser beam (Flood, 2001).

Most of the research on vegetation studies using lidar has been in forestry and can be divided into stand-based and individual tree-based studies. Stand-based studies have focussed on extracting characteristics like canopy height, canopy openness and tree-species composition and derived information like average stem diameter, forest biomass, Leaf Area Index and canopy volume (Harding et al., 2001; Hollaus et al., 2006). Individual tree-based studies mainly look at location, crown delineation, height and species identification (Holmgren and Persson, 2004; St-Onge, 1999; Suárez et al., 2005). These studies were based on lidar data alone, or lidar with optical imagery

(Bork and Su, 2007; Hill et al., 2002; Hill and Thomson, 2005; Hyde et al., 2005). There are only a few studies, which have looked at mapping vegetation, including low vegetation, for topographical mapping from lidar data.

The classification of vegetation points from lidar point clouds is considered to be a challenge, especially in the case of low vegetation, and is a focus of current research. The analysis of discrete return data relies on the spatial relationship of the points. However, the full-waveform data give additional information about the objects in the path of the laser pulse (Wagner et al., 2006). This could lead to the development of classification methods based on the information from each point with less reliance on spatial relationships, which would simplify the processing significantly. Many analytical waveform solutions are based on Gaussian decomposition (Hofton et al., 2000; Wagner et al., 2006). The assumption is that the scattering properties of a cluster of targets can be described by a Gaussian function. An extended target could be described by a series of Gaussian functions, where each pulse represents a cluster of targets too close to be differentiated. This method gives estimates of the location and scattering properties of the targets. These include pulse width, amplitude, range and cross-section of each detected echo, and the number of returns and total cross-section of each laser pulse (Wagner et al., 2008).

Some of these attributes, which are direct properties of the return signal, have been used for distinguishing vegetation and non-vegetation points from full-waveform data (Ducic et al., 2006; Wagner et al., 2008). Their values, however, could be dependent on the method of waveform decomposition used.

Classification mainly employs parametric classification, decision-tree approaches and k-means clustering. Ducic et al. (2006) used a decision tree, but could classify the returns only into vegetation and non-vegetation due to the difficulty in separating trees and shrubs (vegetation) from grass, roof and road (non-vegetation). This could be because their aim was to classify points without using elevation or relationship to adjacent points.

Charaniya et al. (2004) have been able to classify discrete return lidar data into trees, grass, roads and building roofs with a classification accuracy of 66% - 84%. In their study, the lidar data were interpolated to a regular grid, and classification was based on normalised height, height variation, multiple returns, luminance and intensity. The luminance values were obtained from an additional grey scale aerial image.

Increasingly further attributes of the surface derived from the lidar, e.g. roughness and mean slope etc., are used for classification. Miliaresis and Kokkas (2007) employed parametric classification and k-mean clustering for the extraction of building and vegetation classes from lidar DEMs based on elevation, roughness, mean slope and standard deviation of the slope of grid cells.

This study classifies points based on parameters extracted from full-waveform data into vegetation, roads and building roofs. The classified points are converted to polygons by dissolving Thiessen polygons based on the estimated class. The points within the vegetation polygons will be analysed in future work to classify vegetation itself into different sub-classes to be represented within a three-dimensional topographical map.

2. Study Area and Dataset

A full-waveform lidar dataset was obtained, over the Avonmouth area of Bristol, using LiteMapper5600 Airborne Lidar Terrain Mapping System in August, 2006. The study area is 1 km^2, from Easting 354000 to 355000, and Northing 178000 to 179000 (OS British National Grid coordinates), which includes a range of land use and landcover types. In addition to stands of

trees, there are trees along the road, shrubs in gardens in the residential areas as well as grassland. The land use includes residential, commercial and institutional areas and agricultural land.

The LiteMapper system makes use of RIEGL LMS-Q560 laser scanner, and data were captured at a height of approximately 950m above ground level. The point density ranged from 0.5-0.8 points per m^2 per flightline. Four flightlines, with overlaps, covered the whole study area. The raw waveforms were decomposed using the standard method, Gaussian Pulse Fitting, available in the commercial package RiAnalyze™ 560. RiWorld™ 560 was used to transform the data into WGS Cartesian coordinates. This was converted to British National Grid before further analysis.

The extracted points were displayed in ArcMap™ using the various attributes. All the returns were made use of for the analysis, which along with the overlapping swath widths of the flight lines generated above 1000000 points giving an average point density of approximately 1 point per m^2. The topographic features could be distinguished to a certain extent by displaying points by elevation, amplitude, pulse width and the number of returns (Fig. 1). Elevation from mean sea level is calculated from the location and orientation of the sensor, and the distance or range to the target. The amplitude is a measure of the strength of the return pulse. The pulse width refers to the standard deviation of the pulse in the Gaussian decomposition. The number of returns denotes whether the point is one of a single, two, three or more hits of a single emitted pulse.

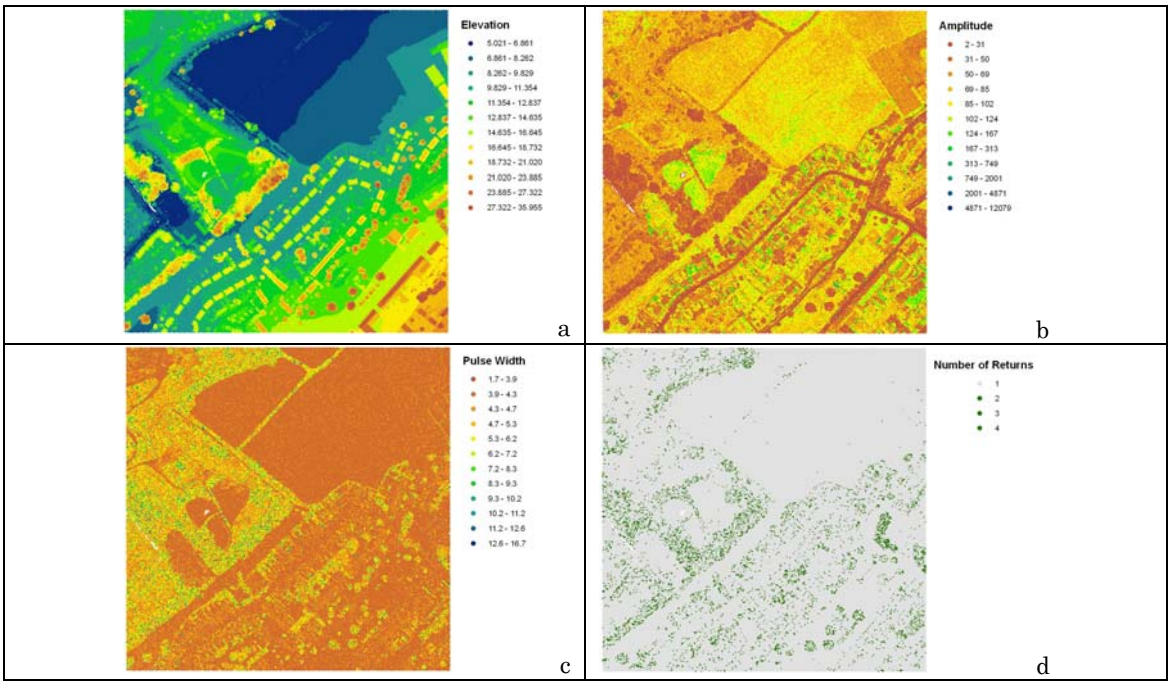

Figure 1: Lidar Points displayed by elevation (a), amplitude (b), pulse width (c) and number of returns (d) The extent shown is a subset of the original dataset from Easting 354000 to 354500 and Northing 178250 to 178750.

3. Methodology

Attributes of individual points as well as attributes based on the spatial relationship of points to neighbouring points were used in the classification process. Amplitude, pulse width and the number of returns of each point were used as attributes of the individual points. A Triangulated Irregular Network (TIN) was created from all the extracted points. Local height variation of a

point was taken as the difference between the maximum and the minimum elevation values of the nodes of TIN triangles attached to each point. Variation of slopes and aspects of attached TIN triangles were used to analyse whether the different surfaces could be separated. The parameters considered were average and standard deviation of slopes and aspects.

An approximate terrain model was created from the lidar points making use of the lowest point in a 10m grid. A TIN was created from these points. There were a few outliers, which were removed manually. They could be identified as nodes of the triangles with steeper slopes or with higher elevation than the surrounding points. These were removed in two steps by creating a TIN after each selection. The final TIN, generated from the selected points, was converted to a 2m grid. The terrain elevation was subtracted from the elevation of each point to get the elevation of the point above the ground, or the normalised elevation.

The topographic features can broadly be classified into natural and man-made features. The natural features consist mainly of vegetation and were divided, based on the elevation, into low (<0.5m), medium (0.5 – 2.5m) and high (>2.5m). The intervals were chosen based on the approximation of terrain elevation and the assumption that building roofs are higher than 2.5m. The man-made features were divided into roads and buildings. The buildings were sub-divided into those with flat and pitched roofs. Training polygons were created for the above six landcover classes using lidar points and an ortho-rectified aerial image. The training polygons contained 16378 points in all, out of which 9835 were vegetation points, 2367 road points and 4176 building points.

The lidar points were classified using five methods. First we used a k-means clustering requiring 12 clusters. In the second method, the means of the attribute values for the various classes in the training dataset were given as the seed points for clustering. The first four principal components of the data were seen to represent 79% of the total variance of the original data, and were used for unsupervised classification in the third method. Next, the means of the canonical variables grouped by the landcover type were used as initial cluster centres for classification. Elevation was grouped into three – less than 0.5m, 0.5 to 2.5m and greater than 2.5m – and a classification was done using this instead of the actual elevation from the terrain for each of the above methods. The last method involved generating a decision tree using the training dataset for classifying the lidar points into the six classes (Figure 2). The significance of the attributes was analysed by taking out one attribute at a time and testing the accuracy of the classification, maintaining similar number of nodes for the decision tree.

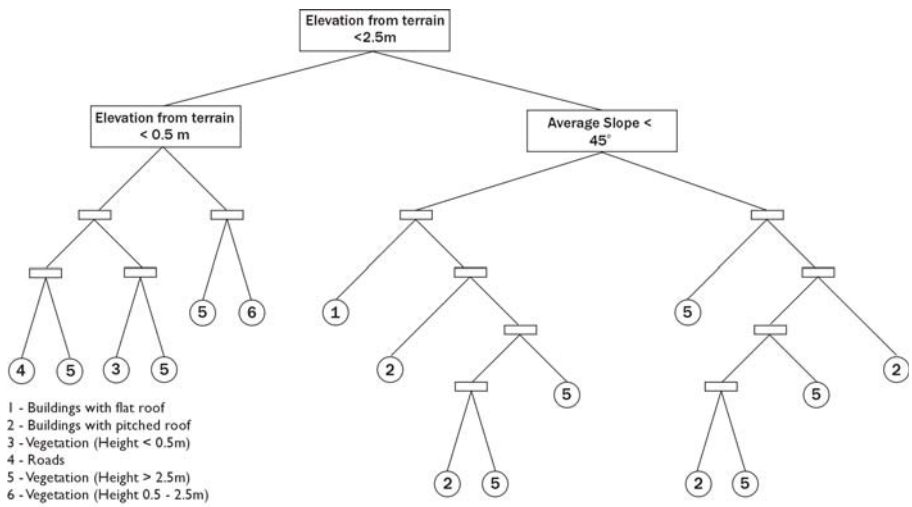

Figure 2: The pruned decision tree for classification

4. Results

Landcover maps were generated using the various classification methods (Fig. 3a-e). Some of the misclassifications become evident on visual analysis, and some by comparing with OS MasterMap™ polygons and an aerial photograph (Fig. 3f-g).

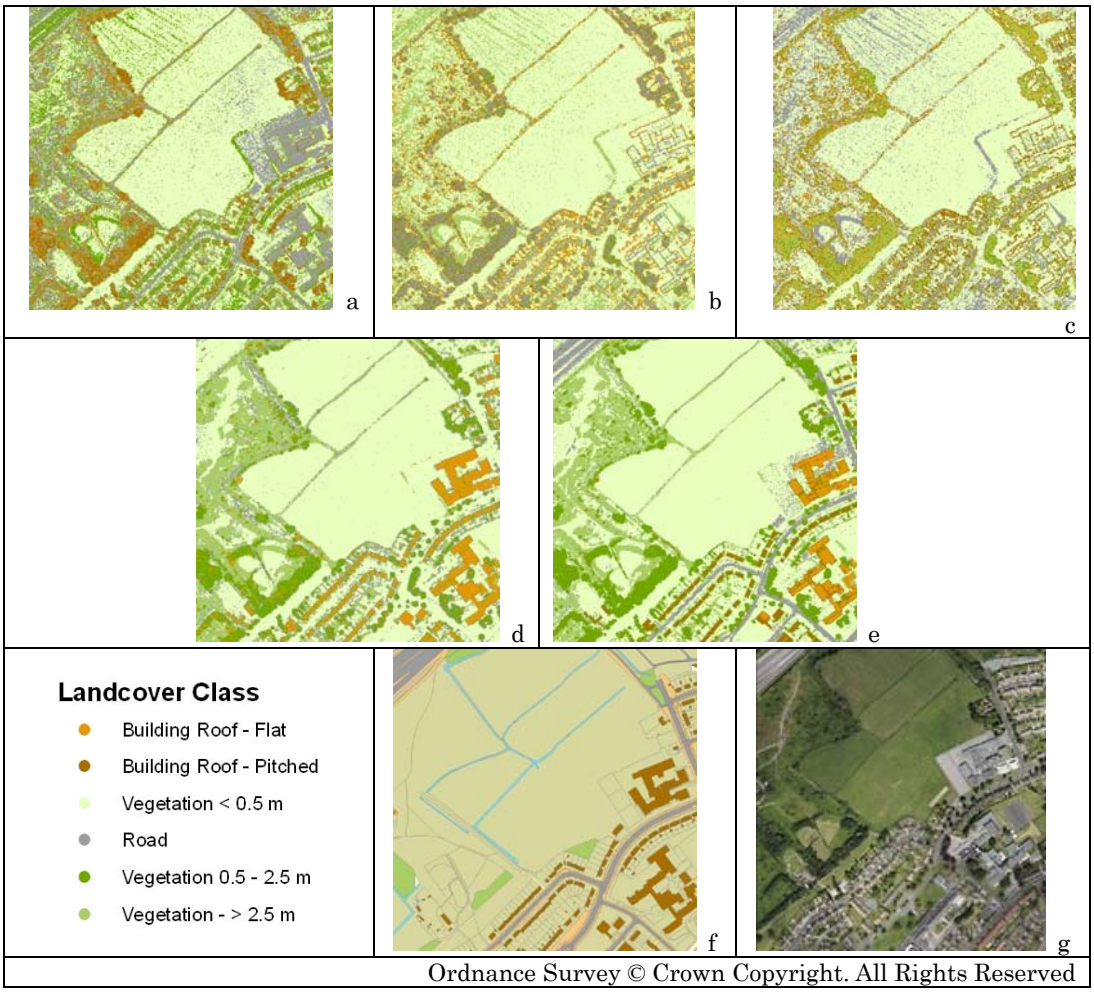

Figure 3: Landcover maps generated using the classes from a) unsupervised k-means classification, b) unsupervised classification with attribute means from the training dataset as seed points, classification using c) variables from principal components analysis, d) canonical variables, e) decision tree classifier and f) OS MasterMap™, g) Aerial Photograph

Table 1 shows the number of correctly classified points from each category, and the overall accuracy for each method. The accuracy assessment makes use of only the training data. Only 36% of the points were correctly classified by the first method. All the flat roofed buildings were misclassified, and the accuracy was very low for trees (3%). The accuracy was the highest for grass and road (88% and 84% respectively). The overall accuracy of the classification increased to 58% in the second method though the accuracy was still low for flat roofed buildings. The misclassification between pitched roofs and trees decreased with this method. The overall accuracy using principal components was higher than that of the first classification, but lower than that of the second. There was an increase in the classification accuracy for pitched roofed buildings and trees. The overall accuracy from canonical variables was almost double of that using the principal components. The accuracy of classification of flat-roofed buildings increased from 0 to 93%. The significant misclassification was that of shrubs as grass.

Table 1: Overall accuracy for k-means Classifications

	Veg < 0.5m	Veg 0.5 – 2.5m	Veg > 2.5m	Roads	Flat Roof	Pitched Roof	Overall Accuracy
Method 1	2189	412	166	1989	0	1139	35.99 %
Method 2	2078	754	2100	2188	1	2440	58.38 %
Method 3	2009	59	817	2095	0	2286	44.36 %
Method 4	2420	930	4979	2207	628	3202	87.72 %
Number of points	2496	1927	5412	2367	674	3502	16,378

Grouping the elevation attribute into three, increased the classification accuracy from 36% to 54% for the first, from 58% to 60% for the second and from 88% to 94% for the fourth method. However, for the third method based on principal components, the accuracy reduced from 44% to 40%.

The overall accuracy of the classification using the decision tree on the training dataset was 98% (Table 2). The pruned decision tree does not make use of the two attributes, standard deviation of aspects and the number of returns. It was seen that the classified elevation and amplitude contributed the most to the accuracy of the classification. Excluding elevation from the decision tree reduced the overall accuracy to 80% and excluding amplitude reduced the accuracy to 88%. Excluding pulse width reduced the accuracy only slightly from 98.1% to 97.65%.

Table 2: Error Matrix for Classification using the pruned Decision Tree
The accuracies are for the data used in the training dataset on a train-all-test-all basis.

	Veg < 0.5m	Veg 0.5 – 2.5m	Veg > 2.5m	Road	Flat-roof	Pitched-roof	User's Accuracy
Veg < 0.5m	2492	3	0	1	0	0	99.84
Veg 0.5 – 2.5m	1	1922	4	0	0	0	99.74
Veg > 2.5m	0	1	5268	0	1	142	97.34
Road	36	7	28	2296	0	0	97.00
Flat-roof	0	0	0	0	670	4	99.41
Pitched-roof	0	0	152	0	13	3337	95.29
Producer's Accuracy	98.54	99.43	96.63	99.96	97.95	95.81	98.10

5. Discussion

The height variation is a measure of the roughness of the surface and is expected to be high for vegetation. This was seen to be more useful than standard deviation and absolute deviation from the mean of elevations within a window in the case of rasterised data (Charaniya et al., 2004). Local statistical variation of attributes of grid cells has been used for separating buildings from other surfaces (Alharthy and Bethel, 2002; Miliaresis and Kokkas, 2007). This was adapted for point data by making use of the variation of attributes of TIN triangles attached to a point. Out of these, the average aspect was found to be of not much use since even flat surfaces could have minor differences in their aspects.

Box-and-whisker plots were used to analyse the various attributes grouped into categories. The amplitude values of roads and trees seem to be lower than that of grass, shrubs and buildings. Though the values overlap, amplitude seems to be a useful attribute in separating roads from low vegetation. The pulse widths are higher and of a wider range for vegetation than for grass, roads or buildings as seen from earlier studies (Ducic et al., 2006). The number of returns is more than one for vegetation and building edges. There are some multiple returns from roads, which could be from overhanging vegetation or vehicles.

The normalised elevation, or elevation from the estimated terrain, is useful in separating buildings from the other classes, especially road and grass. The lower outliers in vegetation are probably from, or close to the ground. The mean slope of the TIN triangles, which has the point as the common node, seems useful in identifying trees, which have larger height variations and hence, higher average slopes. The higher values of the outliers in the roads could be from vehicles, or branches of trees. The standard deviation of slopes of TIN triangles attached to a point is lower and less variable for road, grass and buildings with flat roof. This additional attribute is expected to aid in the correct classification of surfaces if the terrain itself is sloping. The standard deviation of aspects of attached TIN triangles was found to be lower for buildings with pitched roofs than those with flat roofs. This could be because even for a relatively flat horizontal surface, there are minor variations in the aspects. This is less pronounced in sloping roofs. However, this is only of limited use since this is not applicable in the case of ridges and features on the pitched roof. Nevertheless, this attribute is included as the separation of vegetation and pitched roof seems to be the most difficult, and it could be useful in the classification process.

A matrix of scatter plots of the various attributes, grouped by the landcover classes, was generated to analyse the inter-relationships between the attributes. Amplitude and average slope seem to bring out the best separation between the classes. Some of the derivatives of elevation – height variation, average slope, standard deviation of slope and standard deviation of aspect – seem to have a high correlation (Table 3). The average slope has a high correlation with elevation as well as height variation, which is to be expected.

Table 3: Matrix of correlation coefficients of the attributes

	Amplitude	Width	Elevation	Av_slope	Std_slope	Std_aspect	Ht_var	Num
Amplitude	1							
Width	-0.3	1						
Elevation	-0.28	0.34	1					
Av_slope	-0.43	0.38	**0.75**	1				
Std_slope	-0.19	0.29	0.45	0.44	1			
Std_aspect	-0.13	0.05	-0.09	-0.03	0.02	1		
Ht_var	-0.38	0.29	0.54	**0.77**	0.26	0.04	1	
Num	-0.4	0.07	0.28	0.57	0.12	0.07	0.42	1

5.1 Classification by clustering

Cluster analysis groups objects into clusters or groups based on the similarity of their attributes. The k-means method is considered to be suitable for clustering large amounts of data. It partitions the observations in the data into k mutually exclusive clusters in a c-dimensional space where c is the number of attributes used in the classification process (Mathworks, 2008a; Miliaresis and Kokkas, 2007). The required number of clusters, k, has to be provided by the user.

Subtractive clustering is an algorithm for estimating the number of clusters and the cluster centres in a dataset. The range of influence of the cluster centre has to be specified for each dimension, and 0.2 to 0.5 is considered to be the optimum range of values. A value of 0.5 would mean that the range of influence is half the width of the data space for the particular attribute (Mathworks, 2008b). Values from 0.2 to 0.5 were considered for the range of influence with an increment of 0.1. The number of estimated clusters were 12, 7, 4 and 3 respectively. Twelve clusters were considered for further work since it would be easy to re-classify this into the six landcover classes.

The attribute values were transformed using z-score to standardise the differing value ranges of the attributes. In z-score transformation, the mean of the attribute values is subtracted from the data value and the resulting value divided by the attribute standard deviation. The training dataset was partitioned into twelve clusters in the first method. The initial cluster centroid positions are chosen at random by the k-means classifier, and the classification would differ depending on the location of the seeds. To avoid this, the cluster centres generated by subtractive clustering were used as the seed points. The clusters were then re-classified into the six landcover classes based on their proximity to the mean of the attribute values for the different classes in the c-dimensional space. This was done by a k-means classification of the centroid locations, with six as the desired number of classes and the attribute value means as the seeds. In the second method, the attribute value means from the training dataset were chosen as the initial cluster centres.

As shown by the correlations between attributes (Table 3) there is some redundancy in the information content of the whole data set. Principal components analysis is a method to reduce this by generating a new set of variables. All the principal components are orthogonal to each other and each component is a linear combination of the original variables. As in the unsupervised classification, the number of clusters was determined by subtractive clustering. Six clusters were identified, and the k-means classification was done using the mean attribute values of the transformed dataset from subtractive clustering as seed points. The six clusters were reclassified into the six landcover classes as earlier based on their proximity.

The canonical variables are linear combinations of the original variables, chosen to maximize the separation between groups, or the six landcover classes. Among all possible linear combinations, the first canonical variable has the maximum separation between groups. The second canonical variable has the next maximum separation subject to it being orthogonal to the first, and so on. The first four canonical variables were used for the k-means classification with the means of the canonical variables as the seed points.

5.2 Classification Using Decision Tree

The first four methods are based on the assumption that the populations of each group are normally distributed. Decision trees offer a non-parametric alternative and do not require such assumptions or simplifications. The attributes – amplitude, pulse width, elevation class, average slope, standard deviation of slopes, standard deviation of aspects, height variation and the number of returns – were used as the input for creating a classification tree. Maximum deviance reduction was chosen as the splitting rule for generating the decision tree. This created a decision tree with a large number of nodes, which clearly over-fitted the training dataset. The dataset was partitioned into ten random subsamples. For each subsample, a tree was fitted to the remaining data, which was then used to predict the subsample. This was used to derive an optimum level of pruning for the decision tree (Mathworks, 2008b). The 'best' level appeared to change with each trial due to the random selection of the subsamples. So, the mode of the best pruning level out of hundred was selected. The original decision tree contained 491 nodes, which was pruned to 31 nodes with a pruning level of 23. This decision tree was used to classify the original dataset.
As seen from the decision-tree diagram, it is difficult to separate buildings with pitched roofs and vegetation higher than 2.5m. This was mainly for the building edges and features like chimneys on the roof. Medians on roads, marked in a lighter colour, have higher amplitudes and are classified as low vegetation. Similarly, some of the vehicles are classified as vegetation of medium height. Some points on trees, possibly with dense foliage, are classified as buildings. It can be seen from the MasterMap data that some of the buildings are not detected, and are classified as vegetation of medium height. This is mainly because some of the smaller buildings are less than 2.5m in height.

6. Conclusion and Future Work

We show that a decision-tree classifier performs significantly better (98% accurate) than k-means clustering (88%) based on the train-all-test-all accuracy. Though it was seen that the standard deviation of aspects and the number of returns were not as useful as expected, it could be due to the selected classes. Standard deviation of aspects could be useful in segmenting the pitched roofs for roof modelling and the number of returns could be useful in sub-classifying vegetation. The average slope and height variation are dependent on the point density, and the pulse width depends on the method of waveform decomposition. These will have to be modified for other datasets. Amplitude is dependent on various factors like the sensor, flying altitude, incidence angle and surface reflectance. Amplitude, corrected for these factors, would be a useful attribute if the classification method is to be applied on other datasets. The classification could be further improved based on the spatial relationships between the classified polygons (de Almeida et al., 2007). Further work is required to test the accuracy of the classification on untrained data.

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