TERRAIN AND CANOPY SURFACE MODELLING FROM LIDAR DATA FOR TREE SPECIES CLASSIFICATION

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Abstract

It has been recognised that airborne LiDAR (light detection and ranging) offers advantages over the interpretation of aerial photographs and processing of multi-spectral and/or hyper-spectral remote sensing data in forest classification. LiDAR with capability of canopy penetration yields such high density sampling that detailed terrain and canopy surface models can be derived. Recent success in forest classification using LiDAR derived products including terrain and canopy surface models has been reported in many studies. However, there is still considerable scope for further improvement in classification accuracy by taking maximum advantage of the information extracted from LiDAR data and by employing more efficient classifiers such as support vector machines (SVMs). This study aims to use LiDAR data to generate digital terrain and canopy surface models to identify the location and crown size of individual trees for the species classification of Australian cool temperate rainforest dominated by the Myrtle Beech (*Nothofagus cunninghamii*) and neighbouring Silver Wattle (*Acacia dealbata*). The tree species classification was achieved by employing LiDAR-derived structure and intensity variables via linear discriminant analysis (LDA) and SVMs. The results showed that the inclusion of LiDAR-derived intensity variables improved the accuracy of the classification of the Myrtle Beech and the Silver Wattle species in the study area. It demonstrated that the SVMs have significant advantages over the traditional classification methods such as the LDA methods in terms of classification accuracy.

Keywords: LiDAR, LiDAR intensity, canopy surface model, support vector machines, forest classification

INTRODUCTION

Airborne light detection and ranging (LiDAR), also referred to as airborne laser scanning (ALS), is one of the most effective means of terrain data collection. Using LiDAR data for the generation of digital terrain model (DTM) (or digital elevation model (DEM)) is becoming a standard practice in the spatial science community (Liu, 2011). There has been increasing interest in the application of airborne LiDAR for the analysis of forest structures and the classification of forest type over the last decade (Popescu et al., 2002; Zimble et al., 2003; Goodwin et al., 2006; Ørka et al., 2009; Suratno et al., 2009; Vauhkonen et al., 2009; Junttila et al., 2010; Korpela et al., 2010b; Korhonen et al., 2011; Zhang et al., 2011). LiDAR applications in forest classification mostly refer to either the structural description at plot or stand level or to single tree identification (Holmgren et al., 2003; Hyyppä et al., 2008; Hawbaker et al., 2010; Lindberg et al., 2010). As high-density LiDAR data became more readily available, the scope to single tree identification and species classification became more obvious. From dense LiDAR points, individual trees can be identified. Typically, individual tree crown outlines are extracted from a LiDAR-derived CHM (canopy height model) (Brandtberg et al., 2003; Holmgren and Persson, 2004; Popescu and Wynne, 2004; Ørka et al., 2009) such that the LiDAR point cloud within the individual crown outlines become the key to deriving the variables relevant to tree species classification. These variables are derived either from LiDAR height measurement or LiDAR intensity values. The basic idea of using structure/height and intensity variables for tree species classification is that different species have different crown properties (Ørka et al., 2009). The vertical distribution and configuration of the forest components are forest type dependent (Brandtberg et al., 2003). The structural differences will affect the distribution of the laser returns from the forests (Ørka et al., 2009). Therefore, the variables derived from the LiDAR data can be used for tree species identification and forest type classification. Height (or structure) related variables usually included crown height, crown depth, mean crown height and crown density (Heurich and Thoma, 2008).

In addition to the three-dimensional coordinates, most LiDAR systems also capture the intensity of the backscattered laser pulses (Wehr and Lohr, 1999; Liu, 2008). The back-scattered laser signal is converted to an electrical signal by a photodetector (typically an avalanche photodiode). The generated photocurrent or voltage is then quantized to a digital number (usually expressed in percent value, representing the ratio of strength of reflected light to that of emitted light or by scaling the minimum and maximum values to a 8-bit (0-255) grayscale palette) which is referred to as the LiDAR intensity value for a particular return (Liu, 2008; Korpela et al., 2010a). Most commercial LiDAR systems used for topographic and forest mapping use lasers that emit energy in the near infrared range of the electromagnetic spectrum. Vegetation reflects this wavelength well (Lillesand et al., 2008; Kim et al., 2009). It has great potential that the LiDAR intensity values could assist tree species classification (Ørka et al., 2009). The LiDAR intensity of forest canopies is influenced by many factors including the reflectance, density, size and orientation distribution of foliage and system settings (Korpela et al., 2010a). Applications of LiDAR intensity data in tree species identification have been attempted in several studies (Holmgren and Persson, 2004; Moffiet et al., 2005; Brandtberg, 2007; Kim et al., 2009; Ørka et al., 2009; Korpela et al., 2010a). It has shown great potential that the LiDAR intensity values could assist tree species classification (Ørka et al., 2009).

Recent success in forest classification and tree species identification using LiDAR-derived variables has been reported in a few published articles. However, there is still considerable scope for further improvement in classification accuracy. Furthermore, the problems associated with satisfying the assumptions that underlie traditional classification methods have also driven research into nonparametric alternatives such as neural networks, decision trees, and more recently support vector machines (SVMs) (Foody and Mathur, 2004a). The SVMs have recently attracted the attention of the remote sensing community (Huang et al., 2002; Foody and Mathur, 2004a; Tso and Mather, 2009; Heikkinen et al., 2011; Mountrakis et al., 2011) and have been attempted to LiDAR-derived variables in forest applications (Koetz et al., 2008; Korpela et al., 2009; Angelo et al., 2010; Chen and Hay, 2011; García et al., 2011; Zhao et al., 2011). SVMs originated from the principle of statistical learning theory and its foundations were introduced by Vapnik (Vapnik, 1998; Vapnik, 2000). The simplest nature of classification with a SVM is for the situation in which the two classes are linearly separable (Foody and Mathur, 2004b). The core operation of SVMs is to construct an optimal hyperplane that separates the two classes in such a way that the distance from the hyperplane to the closest training data points in each of the classes is as large as possible (Vapnik, 1998; Tso and Mather, 2009). The hyperplane is determined in a SVM to maximize the generalization ability. However, if the input data are not linearly separable, the obtained classifier may not have high generalization ability (Abe, 2010). For nonlinear decision surfaces, the input data are mapped into a high-dimensional feature space via nonlinear vector mapping function by introducing a variety of kernels, in order to spread the distribution of the data in a way that facilitates the fitting of a linear hyperplane (Tso and Mather, 2009; Abe, 2010). The selection of kernel function and appropriate values for corresponding kernel parameters, referred to as kernel configuration, may affect the performance of the SVMs (Huang et al., 2002). Among many developed kernels (Schölkopf and Smola, 2002), the radial basis function (RBF) is widely used (Tso and Mather, 2009). The only one parameter to be predefined for RBF is γ which controls the width of the kernel. The accuracy of classification by a SVM is dependent on the proper selection of the magnitude of the parameters C and γ (Foody and Mathur, 2004a). C is a penalty parameter (or cost parameter) to be determined by the user, which determines the trade-off between the maximization of the margin and the minimization of the classification error (Abe, 2010). For details of SVMs and applications in remote sensing, readers are referred to Vapnik (1998), Abe (2010), Chang and Lin (2011), Foody and Mathur (2004a) and Tso and Mather (2009). The overall objective of this study is to use LiDAR data to generate digital terrain and canopy surface models to identify the location and crown size of individual trees for the species classification. The specific objectives are to examine the contribution of the LiDAR intensity variables to the classification results and evaluate the performance the SVMs for the tree species classification.

MATERIALS AND METHODS

Study area

The study area is in the eastern Strzelecki Ranges, southeast Victoria, Australia (Fig. 1). The Strzelecki Ranges (formerly known as the Great Forest of South Gippsland) are an isolated series of mountains in the southern section of the Gippsland region. Prior to European settlement the Strzelecki Ranges were densely vegetated by wet forest (also referred to as wet sclerophyll forest) and cool temperate rainforest. Wet forest is most commonly dominated by Mountain Ash (*Eucalyptus regnans*) (Davies et al., 2002), characterised by a tall eucalypt overstorey, a broad-leaved shrubby understorey and a moist, shaded, fern-rich ground layer that is usually dominated by tree-ferns (DSE, 2005). In eucalypt-free areas, Silver Wattle may be locally dominant (Davies et al., 2002). Cool temperate rainforest is defined as a closed, non-eucalypt forest, which occurs in high rainfall areas and within wet forest areas which have not been exposed to fire. Myrtle Beech is the dominant species of cool temperate rainforest in the study area. These forests have experienced widespread land clearing since European settlement. Subsequent agricultural abandonment and a frequent wildfire history have resulted in severely disturbed landscape in the Strzelecki Ranges (Noble, 1978; Gullan et al., 1984; Legg, 1986). Rainforest is sensitive to fire and, following fire, is often replaced by forest types dominated by fire tolerant species such as some eucalypts, which rely on fire to open their protective seed pods so that their seeds can germinate (Reichl, 1966; Langkamp, 1987). For example, in the study area, there was extensive regeneration of eucalypt forest following catastrophic wildfires in 1939 and 1944. The landscape has undergone further significant changes with the establishment of large scale plantations in the area since the mid-twentieth century (Littlejohn, 1978; Noble, 1978). Currently, areas bordering cool temperate rainforest in the Eastern Strzeleckis are a mosaic of different land use histories involving both natural and human disturbances, and so a very complex forest structure in the remnant patches of cool temperate rainforest and adjacent forests including wet sclerophyll and plantation forests prevails. This study focuses on an area with cool temperate rainforest distribution in the Eastern Strzeleckis, which covers an area of 1.82 km2 with elevations ranging between 322 m and 448 m.

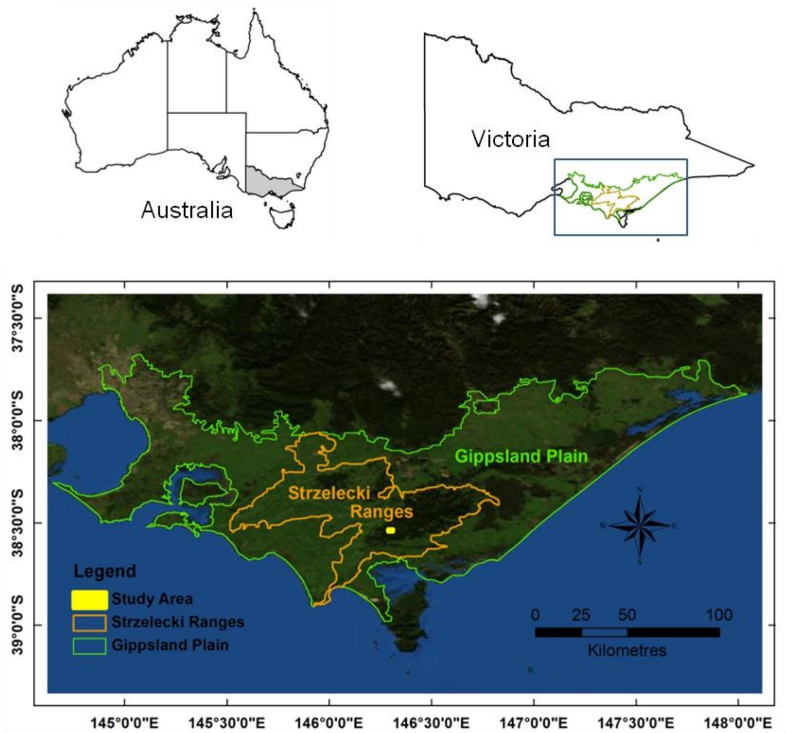

Fig. 1. Study area

Data

LiDAR data were collected using an Optech ALTM Gemini LiDAR system at a flying height of 1,100 m above ground between 11 and 23 October 2009 (for the whole Strzelecki Ranges). The laser pulse repetition frequency is 70 kHz. The laser scanner was configured to record up to 4 returns for one laser pulse. The average point density was 4 points per square metre, and the laser footprint diameter was 0.3 m. The LiDAR data used for this project was documented as 0.20 m for vertical accuracy and 0.25 m for horizontal accuracy. The LiDAR data were classified into ground and non-ground points by the vendor and were delivered in binary LAS 1.2 file format.

Ecological Vegetation Classes (EVCs), which describe the spatial extent of native vegetation types, were introduced by the Victoria Department of Sustainability and Environment in the 1990s. EVC mapping was implemented as part of the regional forest agreements, driven by a need to determine boundaries for a forest reserve system. The EVC mapping was undertaken first by the interpretation of aerial photographs and the process was designed to outline native vegetation patches and any obviously related patterns. The range of aerial photograph patterns was then field checked and lists of plant species were recorded (Davies et al., 2002; Boyle and Lowe, 2004). EVCs are the basic regional scale mapping unit used for forest ecosystem assessments, biodiversity planning and conservation management in Victoria. The EVC data provided by the HVP Plantations Pty Ltd were used as reference data in this study.

Methods

A DEM with one metre horizontal resolution (grid size) was generated using the LiDAR ground data. The highest points of the first returns of non-ground LiDAR data within each one metre square which represent the laser returns from tree canopy were used to generate a canopy surface model (CSM) for the study area. A canopy height model (CHM) was computed by subtracting the DEM from the CSM. The CHM represents the height variance of the top canopy. The TreeVaW software developed by Popescu and Wynne (2003) was used to identify the location and crown size of individual trees from the CHM in the study area. It operates on the assumption that the local maximum height in a spatial neighbourhood represents the tip of a tree crown. Detailed descriptions of the TreeVaW algorithm performance are found in (Popescu et al., 2002; Popescu et al., 2003; Popescu and Wynne, 2004). For each identified tree, the crown diameter for each identified tree was calculated by averaging two lengths measured along two perpendicular directions from the location of the tree top (Popescu and Wynne, 2004). The LiDAR points were extracted for each of the individual trees using a cylinder defined by that tree crown diameter obtained from the output of the TreeVaW. Extracted LiDAR points were used to create tree height profiles representing the spatial distribution of the vertical structure of individual trees. An important tree attribute is the crown base height: the distance measured from the ground to the bottom of the tree crown. The *k*-means clustering algorithm that produces a partition of the data into the *k* different clusters in such a way that all individuals in a cluster are closer to their own cluster mean (Landau and Everitt, 2004; Burns and Burns, 2008) was performed on the height profile to determine the crown base height of each individual tree. It is the LiDAR point data from above the crown base that are used in deriving canopy variables. The variable names and descriptions derived from heights and intensity values of laser returns within tree crowns are listed in Table 1.

One-way ANOVA (analysis of variance), a statistical technique to test whether the observed differences between the sample means are of such magnitude as to indicate that they could have come from the same or different populations (Walford, 2011), was performed on these variables to see if each of these variables can be used to distinguish one tree species from the other. The hypotheses to be tested for a variable in the one-way ANOVA are (Cabrera and McDougall, 2002):

H_0: $\mu_1 = \mu_2$ (the means of a variable from the two tree species are equal)
H_1: $\mu_1 \neq \mu_2$ (the means of a variable from the two tree species are not equal)

The *P*-value in an *F*-statistic for the one-way ANOVA test of H_0 is $P(F < F_{df1,\ df2})$, where df_1 and df_2 are the degrees of freedom and are equal to 1 and 592 in this study (2 tree species and 594 sampled trees), $F_{df1,\ df2}$ is the *F-critical* value with the degrees of freedom df_1 and df_2, and *F* is the observed value of the *F*-statistic

(Cabrera and McDougall, 2002). For a given significance level, usually at α = 0.05 level (so-called at 95% confidence level), the *F-critical* value is the *F* value above which 100α% of the null sampling distribution occurs (Seltman, 2010). Consulting the *F*-distribution table with 1 and 592 degrees of freedom, the *F-critical* value at α = 0.05 level was obtained as 3.841. To retain the null hypothesis at 95% confidence level, the *F* value must be less than 3.841. For any one of the LiDAR-derived variables, if the *F* value is greater than 3.841 (the *P*-value is less than α), the null hypothesis will be rejected. This indicates that for this variable, the mean values from two tree species are significant different. In other words, one tree species can be distinguished from the other by this LiDAR-derived variable.

Table 1. LiDAR-derived structure and intensity variables and description.

Variable	Description
MaxH	Maximum crown height
Depth	Depth (or extent) of tree crown
MeanH	Mean crown height
StdDev	Standard deviation of heights of laser returns within a crown
Density	Ratio of the number of laser returns in the crown to the total number of laser returns within the area defined by a crown diameter
MeanI	Mean intensity value of laser returns within a crown
StdDevI	Standard deviation of intensity value of laser returns within a crown
MeanIF	Mean intensity value of first laser returns within a crown
StdDevIF	Standard deviation of intensity value of first laser returns within a crown

The RBF kernel is used to fit SVMs for the classification of Myrtle Beech and Silver Wattle using LiDAR-derived variables. The RBF kernel parameter *γ* and the penalty term *C* must be properly determined to produce the best classification accuracy. The grid search algorithm (part of the SVM package LIBSVM) (Chang and Lin, 2011) was implemented to find out the suitable parameter values. A grid search over a bounded space (x, y) begins at one corner of the grid and is evaluated with cross-validation at every grid point separated by a value δ until the opposite corner of the grid is reached (Tso and Mather, 2009). An exponentially growing sequences of *C* and *γ* (for example, $C = 2^{-5}, 2^{-3}, \ldots, 2^{15}$, $\gamma = 2^{-15}, 2^{-13}, \ldots, 2^{3}$) was recommended in practice (Hsu et al., 2010). Furthermore, in order to reduce the search time, the algorithm searches and evaluates the parameter values over a coarse grid (i.e., bigger δ). Once identifying a better region on the grid, the search then focuses on a finer grid (smaller δ) on that region (Tso and Mather, 2009; Hsu et al., 2010). The selected parameter values were used in SVMs for tree species classification. The procedures of selection of parameter values and implementation of SVMs for tree species classification with cross-validation were carried out using LiDAR-derived structure variables only, intensity variables only, and both structure and intensity variables. The classification results were compared with those from the LDAs.

RESULTS AND DISCUSSION

The *F*-statistics and p-values from the one-way ANOVA for all LiDAR-derived variables are shown in Table 2. All the *p*-values from one-way ANOVA are less than 0.05. All the *F* values in the one-way ANOVA are greater than the *F*-critical value 3.841. Therefore, the null hypotheses in the one-way ANOVA for all 9 variables should be rejected. The results revealed that it is possible to discriminate two tree species if using any one of the 9 LiDAR-derived variables.

The overall accuracy of the classification results from the LDAs and the SVMs are shown in Fig. 2. It is observed that using LiDAR-derived structure variables, 83.2% of the individual trees of the Myrtle Beech and

Silver Wattle were correctly classified using the LDA. If using only the intensity variables in the LDA, relatively low classification accuracy, 74.6% was obtained. However, if including both structure and intensity variables in the LDA, the overall classification accuracy increased from 83.2% (using only structure variables) to 86.4% (using both structure and intensity variables). The results of this study demonstrated the contribution of LiDAR-derived intensity variables to the identification of the Myrtle Beech and the Silver Wattle tree species at individual tree level. Although relatively low classification accuracy was obtained when only using LiDAR-derived intensity variables, the combination of both the structure and intensity variables in the discriminant analysis allowed individual Myrtle Beech and the Silver Wattle trees to be identified with high accuracy.

Table 2. Statistics results for variables from one-way ANOVA and independent t tests

	MaxH	Depth	MeanH	StdDev	Density	MeanI	StdDevI	MeanIF	StdDevIF
F	192.894	53.319	17.851	143.317	27.424	121.217	90.191	92.909	108.138
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

In comparison with the results of the LDAs, 88.6% of the individual trees of the Myrtle Beech and Silver Wattle were correctly classified by the SVM if using LiDAR-derived structure variables only. An overall accuracy of 75.4% was achieved from the SVM classifier using the intensity variables only, without significant increase compared with the results from the LDA, indicating that the tree species classification results are not promising if using only the intensity variables no matter which classification approach (SVM or LDA) was used. If using both structure and intensity variables, however, the overall classification accuracy increased from 88.6% (using only structure variables) to 92.8%, also indicating the contribution of intensity variables to the improvement of classification results from the SVM classifier.

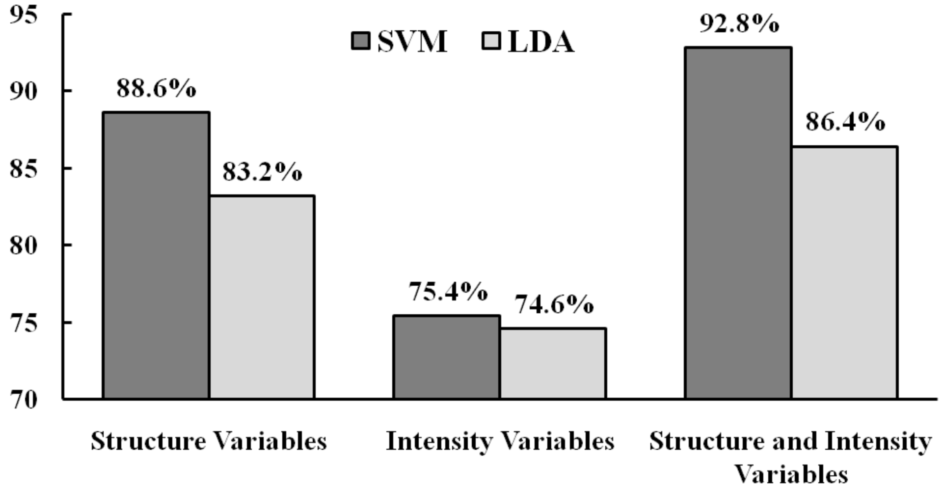

Fig. 2. Overall classification accuracy from support vector machines (SVM) and linear discriminant analysis (LDA) using LiDAR-derived structure variables only, intensity variables only, and both structure and intensity variables.

The acquisition of LiDAR intensity is usually at no extra cost in a LiDAR mission. Therefore, a growing attention has been paid to the application of these valuable intensity data. However, the LiDAR intensity values are affected by many factors such as the flying height, atmospheric conditions, directional reflectance properties, the reflectivity of the target, and the laser settings (Baltsavias, 1999; Liu et al., 2007; Kim et al., 2009). Accordingly, what each intensity dataset can offer to the analyst is not easy to define without at least preliminary exploration after due consideration of LiDAR intensity calibration. It is worth noting that so far most of studies used raw LiDAR intensity data for forest classification (Brandtberg et al., 2003; Holmgren and Persson, 2004; Kim et al., 2009). It is generally believed that as long as the relative intensity values are different between different forest types, the intensity values might be applicable for forest classification (Lovell et al., 2003). It is no doubt that if the intensity data were calibrated properly, there will be a considerable potential to use intensity to improve the application of LiDAR data in forest classification and tree species identification (Donoghue et al., 2007).

It is evident that the SVMs produced higher accuracy than the LDA did. Compared to the LDA method, significant increases in overall classification accuracy were observed by using LiDAR-derived structure variables only or using both structure and intensity variables in the SVMs. If using LiDAR-derived intensity variables only, the overall classification accuracy from the SVM is just slightly higher than that from the LDA. However, with combined use of the intensity and structure variables, the overall accuracy from the SVMs increased from 88.6% to 92.8%, indicating the contribution of the intensity variables to the improvement of classification results.

CONCLUSIONS

This study examined the applicability of LiDAR-derived terrain and canopy surface models for the identification of the location and crown size of individual trees for species classification using LiDAR structure and intensity variables. It demonstrated the success of the SVMs for the identification of the Myrtle Beech (the dominant species of the Australian cool temperate rainforest in the study area) and adjacent tree species – notably, the Silver Wattle at individual tree level using LiDAR-derived structure and intensity variables. An overall accuracy of 92.8% was achieved from the SVM approach. Compared to the overall accuracy of 86.4% from the linear discriminant analysis, it is evident that the SVMs have significant advantages over the traditional classification methods such as the LDA method in terms of classification accuracy. Although the overall accuracy of classification results from both SVM and LDA was relatively low when just using the intensity variables in the analysis, combination of the structure and intensity variables in the discriminant analysis did improve the accuracy of classification results, indicating the contribution of the LiDAR intensity variables to the classification results.

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