Extracting trees in an urban environment using airborne LiDAR

by Andrew Plowright

Abstract

Urban forests represent a considerable financial investment for cities. Despite the efforts and resources expended on the maintenance of trees, cities often lack comprehensive information on their condition. Light detection and ranging (LiDAR), a remote sensing technology already employed in commercial forest management, shows significant potential as a tool for monitoring urban forests. Automated data processing algorithms are required for extracting information at an individual tree basis from LiDAR data. Here, two methods for detecting and delineating trees, variable window filtering (VWF) and multi-scale segment integration (MSI), are applied to two urban plots. The accuracy of both methods is reported in terms of the frequency of errors of omission and commission. Results show a broad variation in the performance between the two methods depending on tree age, species and location. On average, the MSI approach produced fewer errors, which make it a potentially stronger candidate for applications in urban forest management.

Introduction

Light detection and ranging (LiDAR) is an emerging remote sensing technology capable of producing precise three-dimensional models of terrain over broad spatial scales. By emitting a laser pulse and recording the time elapsed until its return, the distance between a LiDAR sensor and a terrestrial feature can be recorded with an extremely high degree of accuracy. Discrete-return airborne LiDAR systems can emit hundreds of thousands of pulses per second which, when combined with the sweeping motion of the scanner and the movement of the aircraft, can sample distances over large swaths of terrain.

LiDAR's capacity to penetrate vegetation has drawn particular interest from the field of natural resource management (Hudak, Evans, & Smith, 2009). LiDAR has been used to characterize forest structure (Coops et al., 2007), estimate carbon stocks (Patenaude et al., 2004), quantify fuel volume (Seielstad & Queen, 2003) and create habitat models (Vierling, Vierling, Gould, Martinuzzi, & Clawges, 2008). From a forest management perspective, perhaps its most promising use is for producing forest inventories

(Woods, Lim, & Treitz, 2008). Area-based approaches (ABA), wherein LiDAR point cloud metrics are used to estimate forest attributes at a stand level, have already been operationalized. ABA have the benefit of requiring data with relatively low point densities, and are thus less costly. However, many modern LiDAR systems are capable of collecting data at densities sufficient to detect and measure individual trees.

Many individual tree detection (ITD) techniques were originally developed using optical imagery (Dralle & Rudemo, 1996; Pouliot, King, Bell, & Pitt, 2002; Wulder, Niemann, & Goodenough, 2000). With its recent introduction into forestry applications, however, LiDAR has become the focus of a large number of studies on ITD. These techniques are either applied to LiDAR point clouds directly, or to products derived from LiDAR data, such as rasterized canopy height models (Jakubowski, Li, Guo, & Kelly, 2013). A common hurdle for ITD is the difficulty of distinguishing separate trees from within continuous canopies. This complication can manifest as errors of omission, when distinct trees are missed, or commission, when non-existent trees are identified. Many different approaches have been tested to locate, and sometimes delineate, individual trees while minimizing both types of errors. Falkowski et al. (2006) used spatial wavelet analysis to extract location, height and crown diameters from a mixed conifer forest. Other methods rely on the integration of LiDAR and other sources of remotely-sensed data. Approaches such as valley following and object-oriented classification have been applied to coregistered LiDAR data and multispectral imagery to detect and isolate individual trees in coniferous forests (Leckie et al., 2003; Suárez, Ontiveros, Smith, & Snape, 2005).

Kaartinen et al. (2012) performed a comparison of several tree detection methods and reported a wide range in the quality of the compared approaches. The study also found that several automated methods outperformed manual processing of LiDAR data in terms of accuracy. It was noted that ITD approaches generally detect dominant or co-dominant trees more consistently than suppressed trees. Jakubowski et al. (2013) compared a vector-based method, which acted on a 3D point cloud, and a raster-based method, which was applied to a canopy height model derived from raw LiDAR data. The study found that the raster-based method tended to detect and outline spurious trees, while the vector-based method presented the opposite problem by under-detecting existing trees.

Most ITD methods were developed for natural or semi-natural forest structures. Previous research has shown that certain ITD techniques perform best in homogenous or near-homogenous stands (Popescu & Wynne, 2004; Schardt, Ziegler, Wimmer, & Wack, 2002). ITD methods requiring calibration based on expected tree morphology are thus best suited for even-aged forests with a narrow range of species.

While forests that are managed for commercial timber may fit this criteria, such conditions are generally not found in urban forests, which may be composed of a wide variety of species and age classes.

While considerable research has been conducted on LiDAR's uses in forestry, its applications in urban forestry are nascent. LiDAR has been used to model solar radiation effects (Tooke, Coops, & Voogt, 2009), map urban tree canopy (MacFaden, O'Neil-Dunne, Royar, Lu, & Rundle, 2012) and estimate citywide carbon storage (Schreyer, Tigges, Lakes, & Churkina, 2014). As LiDAR's utility in the field of urban forestry expands, the need for automated tree detection routines adapted to the urban landscape is likely to increase. Accurate methods for locating and outlining trees are a prerequisite to the extraction of metrics at an individual tree level, such as height or crown density. These metrics can be used for a variety of higher-level analyses, like growth monitoring or the assessment of tree condition.

Here, the performance of two automated tree detection and delineation methods are compared in an urban context. The first is a combination of variable window filtering, used to detect tree tops (Popescu, Wynne, & Nelson, 2002; Popescu & Wynne, 2004) and a marker-controlled watershed segmentation algorithm (Serge Beucher, 1994; Chen, Baldocchi, Gong, & Kelly, 2006), which delineates each tree top's crown. The second is a method that applies Gaussian smoothing to a rasterized canopy height model at multiple scales. The resulting segmentation maps are then integrated to produce a tree crown map that contains segments of multiple sizes (Jing, Hu, Noland, & Li, 2012). Both methods are applied to two urban test plots: a municipal park and a suburban street. The accuracy of both methods is reported in terms of error frequency, and the number and size of the resulting crown outlines are compared.

TEST SITE

Surrey, British Columbia

The city of Surrey is located in the Metro Vancouver Region of British Columbia, Canada. It covers an area of 316.41 km^2. With a 18.6% increase in population between 2006 and 2011 (Statistics Canada, 2011), it is one of the fastest growing cities in Canada.

The city actively manages over 90,000 trees, with an additional 3,500 to 5,000 being planted every year. As part of its annual tree maintenance budget, the city spends C$750,000 on watering alone. Despite the sizeable financial resources expended on its trees, the city's has limited information on the condition of its urban forest at its disposal. City workers currently rely on limited sources of information such as soil condition spot checks when applying watering regimes to drought-stressed trees. Comprehensive information on tree condition at the citywide scale is required to optimize the use of city resources and plan maintenance programs effectively.

Test plots

Two test plots within the city of Surrey were used in this study (Figure 1). The first is a 10 hectare area centered at 48.1142°N and 122.8603°W which contains segments of avenues 61 and 61A in Surrey's Newton subdivison. This plot contains 142 trees maintained by the city. These trees are mostly planted on the sides of low-volume suburban streets. The second plot is centered at 49.1217°N and 122.8652°W, and covers the 2 hectare area of M.J. Norris Park. The 147 city trees in this plot are planted in open, grassy parkland, with the exception of a dense cluster of mature Western redcedar near the middle of the park.

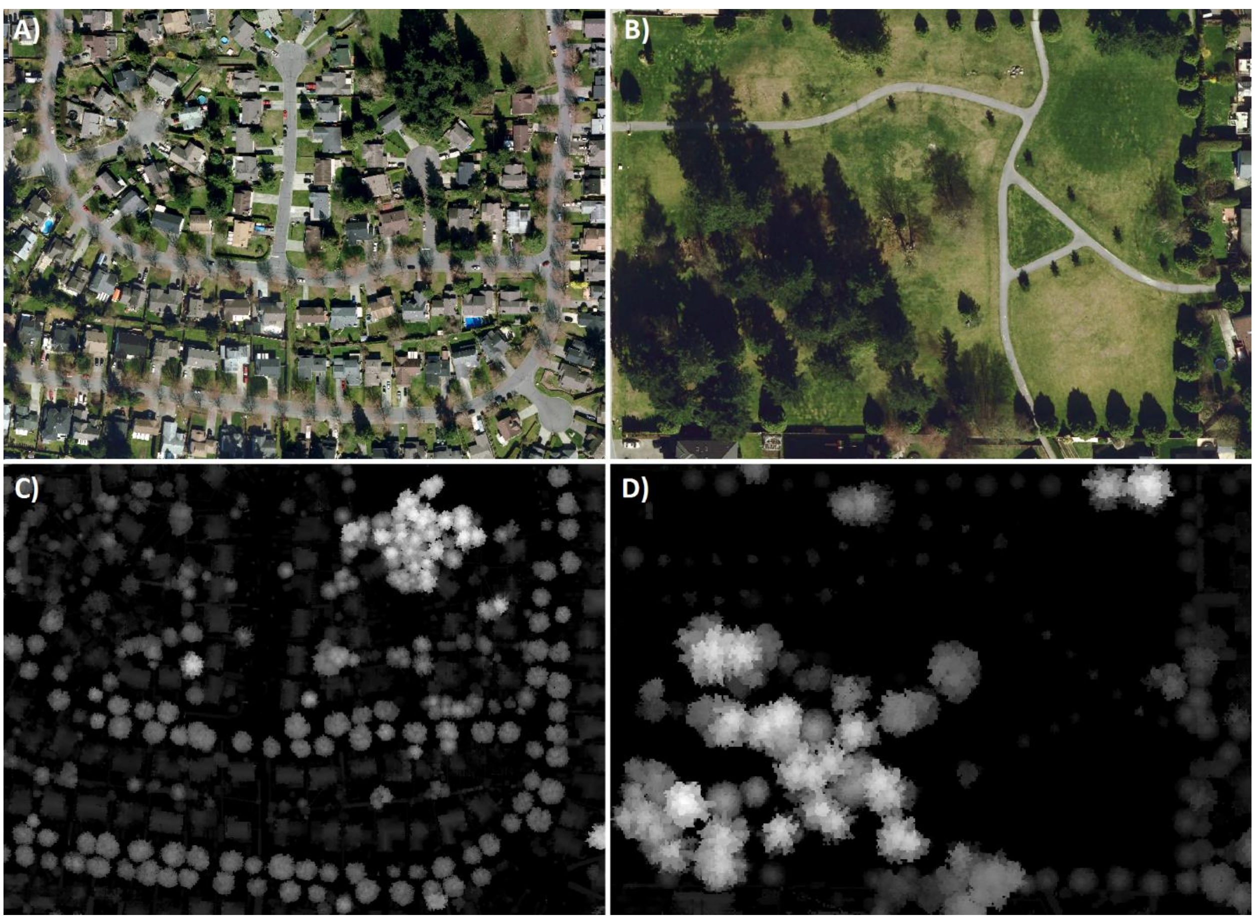

Figure 1. (A) Street plot containing avenues 61 and 61A in Surrey's Newton subdivision. (B) Park plot coterminous with M.J. Norris Park. (C-D) Canopy height models of both plots.

DATA

Field inventory

A geographical information system (GIS) of the city's park, road and tree assets were made available for this project. Included were entries for 90,133 trees maintained by the city. Each entry contained information on the tree's location, age and species. An unquantified degree of error was known to be associated with this database, as field crews had recorded the location of certain trees incorrectly.

LiDAR data

Between April 1st and 11th, 2013, airborne LiDAR data, hyperspectral imagery and digital orthophotography covering the city of Surrey's boundaries were acquired under contract by Airborne Imaging (Calgary, Alberta). The LiDAR system utilized was a Leica ALS70-HP attached to a Cessna Caravan. Average single pass flight line swath was 688m in width, with a 50% overlap between swaths. The LiDAR data was acquired at 1000m above ground level at a pulse rate of 500 KHz, which resulted in an average point density of 25 points per square meter.

The sensor was configured to record up to four discrete returns, which were then separated into different class covers, such as ground, building or vegetation, using TerraSolid software. The contractor delivered a 1m^2 rasterized digital elevation model (DEM) interpolated from classified ground points using a triangular irregular network (TIN). A canopy height model (CHM) was computed using FUSION software by recording the difference in elevation between the highest return of classified vegetation points and the underlying DEM within each cell of a continuous 0.5m^2 grid. The cell value of the CHM corresponds to the maximum above-ground height of vegetation at that location.

METHODS

Watershed segmentation

Both tree delineation methods used in this study incorporate watershed segmentation, an image processing technique developed to outline drainage basins from topographic terrain maps. Conceptually, this technique can be understood as gradually filling basins with water. Where the water of two adjacent basins connects, a boundary is drawn. As the water rises, these boundaries become the outlines of each drainage basin (S. Beucher & Lantejoul, 1979). Because of the morphological similarity between terrain models and tree canopies, this technique has been applied to delineate individual tree crowns from inverted canopy height models (Chen et al., 2006).

Marker-controlled segmentation using a variable window filter

A common problem with watershed segmentation is the issue of over-segmentation, wherein each local maxima of the canopy is outlined, whether it corresponds to a tree top or not. To adjust for this, a variation of the technique known as marker-controlled watershed segmentation can be used (Serge Beucher, 1994). This method constrains the segmentation algorithm using a set of predefined point locations (markers). Segments are drawn around each marker, thus limiting the number of resulting outlines. For this technique to be applied correctly, each marker should correspond to the location of a tree top.

Here, a variable window filter (VWF) was used to determine the point locations of tree tops. VWF has been used to detect tree tops by Popescu et al. (2002) and Falkowski et al. (2006), while (Schardt et al., 2002) and Chen et al. (2006) used it in tandem with a watershed segmentation algorithm to locate and delineate individual trees. This technique applies a moving window to a canopy height model to filter out pixels corresponding to the apexes of trees. A pixel is tagged as a tree top if it has the highest height value within the window. The size of the window varies according to the pixel on which it is centered: a high pixel value will produce a large window and vice versa. This is based upon the positive relationship between tree height and crown width (Popescu & Wynne, 2004).

A set of 30 manually-delineated sample trees were used to obtain the formula for calculating the size of the moving window. The crown of each sample tree was outlined through visual interpretation of the canopy height model. A linear model was then fitted to the average radii of the tree crowns versus their height:

$$Crown\ radius\ (m) = 1.746 \times Tree\ heigt\ (m) + 2.32$$

Using this formula, a VWF was applied to each test plot, which generated a series of tree top point locations. These locations were then used as markers for a marker-controlled watershed segmentation algorithm that generated a set of segments (S_{VWF}).

Integration of multi-scale segments

Another solution to over-segmentation is to apply a Gaussian filter to the canopy height model. The blurring effect of the filter removes many spurious, non-tree local maxima. However, determining the optimal filter size for a given set of forest conditions can be problematic, particularly in an urban setting with a wide variety of tree crown shapes and sizes. Multi-scale image analysis, wherein a single image is blurred at multiple scales, can be used to resolve this difficulty (Hay & Marceau, 2004). Previous studies have successfully used multi-scale approaches to delineate tree crowns from high resolution imagery of forest canopies (Brandtberg & Walter, 1998; Jing et al., 2012; Wang, 2010).

The application of multi-scale segmentation to LiDAR data consists of four steps (Jing et al., 2012). First, the canopy height models of the two test plots are blurred using Gaussian filters of varying intensity levels. Here, sigma values of 0.5, 1 and 2 were used. A watershed segmentation algorithm is then applied to the filtered canopy height models to create multi-scale segmentation maps. The segment boundaries of the coarse-scale segmentation maps are then refined, which is to adjust the boundaries based on the unfiltered canopy height model. This is accomplished by selecting all the unfiltered segments with more than half of the area covered by a given coarse segment. These unfiltered segments are then merged into a new segment, which is used to substitute the boundaries of the coarse segment. This process ensures that the segment boundaries at all scales line up.

Finally, the segments generated at different scales are integrated. This process works under the assumption that irregularly-shaped segments are more likely to represent errors of commission or omission. The integration process aims to minimize the irregularity of the final set of segments. This can be measured using a segment's thinness ratio, which is calculated using the area (A) and perimeter (p) of the segment's polygon (Costa & Cesar, 2009):

$$k = \frac{4\pi A}{p^2}$$

A k value of 1 represents a perfect circle, while lower k value corresponds to more complex shapes. A given coarse segment is compared to overlapping finer-scale segments. If at least two of these finer-scale segments are larger than a threshold A_m, which is the minimum tree crown size expected in the plot, and the coarse-scale segment's k value is lower than a threshold k_m, which is the minimum thinness ratio considered to represent a realistically-shaped crown, then the coarse-scale segment is regarded as representing an error of omission (i.e.: a single segment representing a cluster of trees) and is replaced by the finer-scale segments. Here, a A_m value of 2m^2 and a k_m value of 0.85 were used. This process is applied iteratively over each segmentation map, beginning with the coarsest scale, to ultimately generate a final set of segments (S_{MSI}).

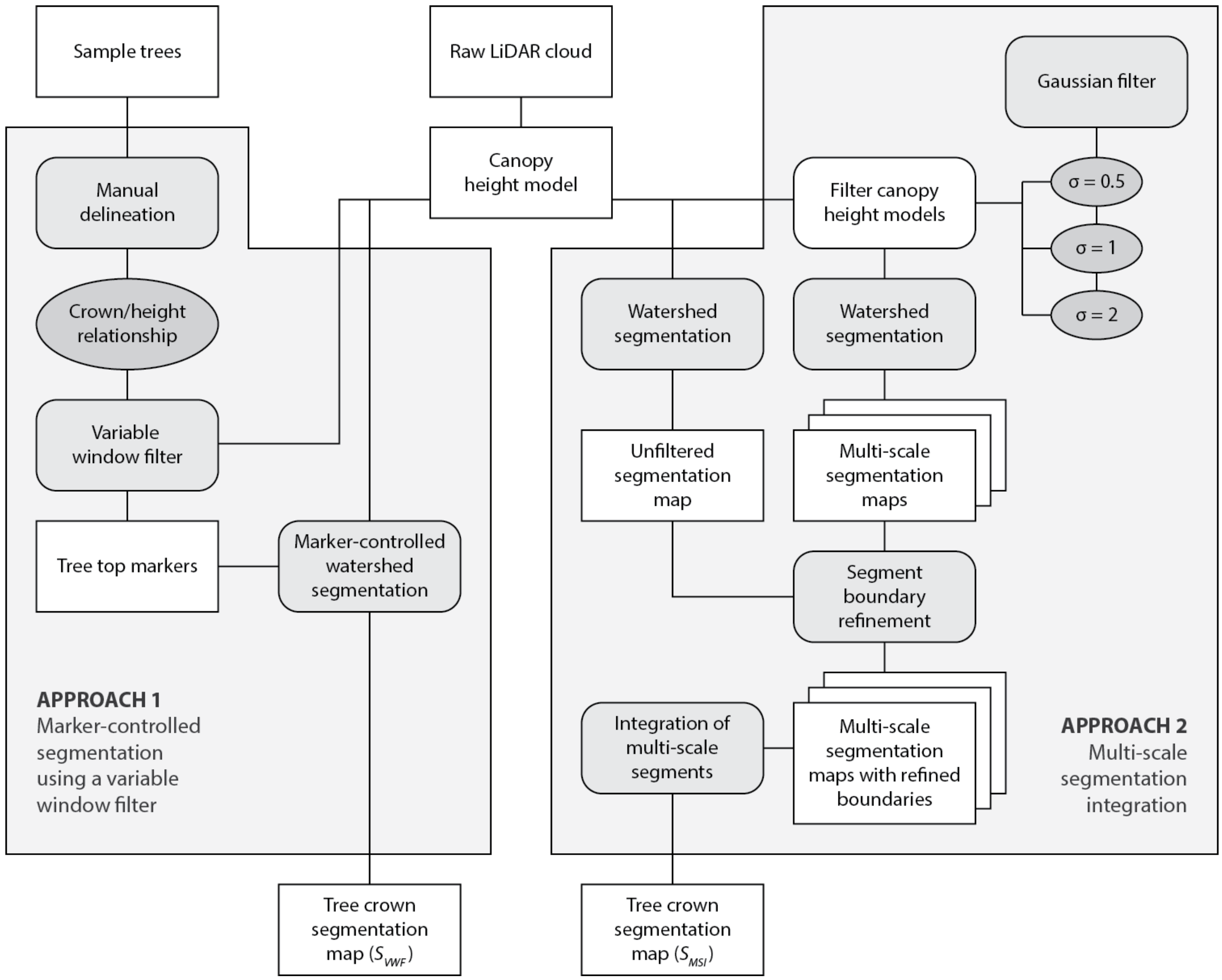

Figure 2. Flow chart of variable window filter (approach 1, left) and multi-scale integration (approach 2, right).

Evaluating delineation performance

Reference data was required to evaluate the performance of the VWF and MSI algorithms. The 30 manually-delineated reference trees were separated into coniferous and deciduous groups (15 trees in each group), and linear models were fitted to each group with tree crown radii as the response variable and tree age as the predictor:

$$Coniferous\ crown\ radius\ (m) = 0.07 \times Tree\ age\ (years) + 0.65$$

$$Deciduous\ crown\ radius\ (m) = 0.2 \times Tree\ age(years) - 1.25$$

Using the tree species and ages recorded in the city's GIS database, tree crown radii were computed for each tree in both plots. These radii were then used to generate a set of circles centered on each tree's point location. While these circles were poor approximations of the tree crowns' actual shape, they could be used to detect basic errors in the delineation algorithms. The test segments S_{VWF} and S_{MSI} were compared to the reference circles, and errors were recorded using the following set of rules:

1) If no test segment has ≥50% of its area within a reference circle, the tree corresponding to that circle is reported as having been missed by the algorithm.
2) If more than one test segment has ≥50% of its area within a reference circle, the tree is considered to be overly segmented, and an error of commission is recorded (Figure 3a).
3) If a single test segment occupies ≥50% of the area of more than one reference circle, then the trees corresponding to these circles are considered to be included within a single segment, indicating an error of omission (Figure 3b).

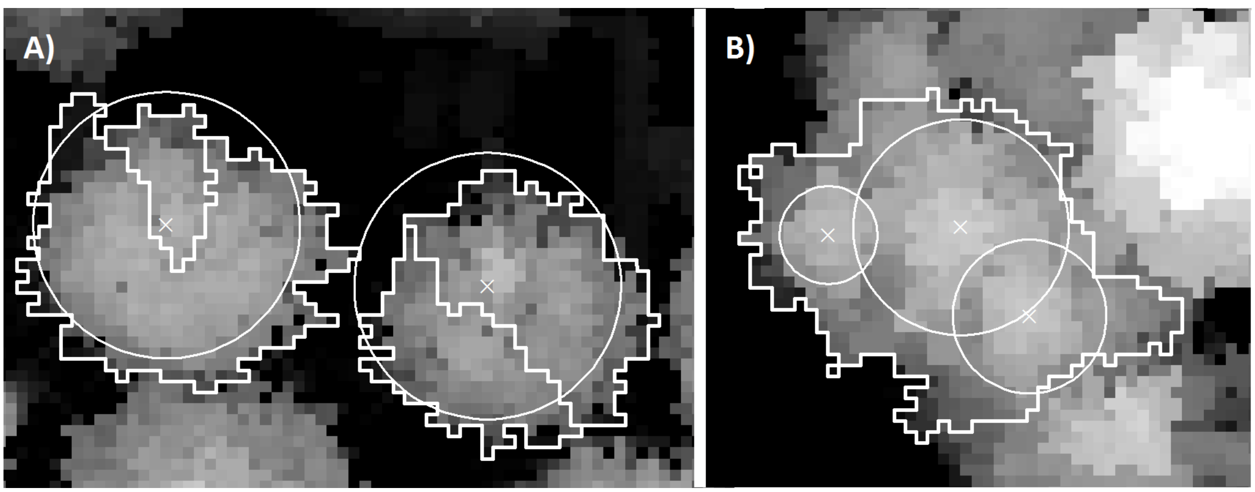

Figure 3. (A) Errors of commission: tree crowns are segmented into multiple segments. (B) Errors of omission: multiple tree crowns are delineated by a single segment.

To investigate the performance of each algorithm on various types of trees and in different locations, errors were reported by dividing the 289 trees between species group: deciduous or coniferous; plot location: park or street; and age class: young trees of less than 20 years of age, and mature trees which are 20 years or older.

RESULTS

Across both plots, the VWF and MSI approaches produced 377 and 270 segments respectively. The average crown size produced by VWF is 58m^2, with a standard deviation of 53.2m^2. MSI produced an average crown size of 110m^2, with a standard deviation of 88m^2.

Table 1. Delineation errors for the variable window filter (VWF) and multi-scale integration (MSI) automated algorithms by tree and location category

		VWF		**MSI**	
		Errors	%	Errors	%
Deciduous	Missing	3	0.02	3	0.02
n = 193	Omission	21	0.11	34	0.18
	Commission	63	0.33	8	0.04
	Total errors	**87**	**0.45**	**45**	**0.23**
Coniferous	Missing	0	0.00	0	0.00
n = 96	Omission	33	0.34	30	0.31
	Commission	0	0.00	3	0.03
	Total errors	**33**	**0.34**	**33**	**0.34**
Park	Missing	2	0.01	2	0.01
n = 147	Omission	48	0.33	54	0.37
	Commission	3	0.02	8	0.05
	Total errors	**53**	**0.36**	**64**	**0.44**
Street	Missing	1	0.01	1	0.01
n = 142	Omission	6	0.04	10	0.07
	Commission	60	0.42	3	0.02
	Total errors	**67**	**0.47**	**14**	**0.10**
Young (<20 years)	Missing	1	0.02	1	0.02
n = 61	Omission	3	0.05	4	0.07
	Commission	1	0.02	7	0.11
	Total errors	**5**	**0.08**	**12**	**0.20**
Mature (≥20 years)	Missing	2	0.01	2	0.01
n = 228	Omission	51	0.22	60	0.26
	Commission	62	0.27	4	0.02
	Total errors	**115**	**0.50**	**66**	**0.29**

Figure 4. Performance comparison between variable window filter (VWF) and multi-scale integration (MSI) by tree and location category. Size of circles are proportional to the number of trees in each category.

Delineation errors for both methods are reported in Table 1. VWF produced errors on 45% of deciduous trees across both plots, most of which were errors of commission (63 out of 87 errors). MSI produced less errors for deciduous trees (23%) but generated more errors of omission than commission (34 and 8 errors out of 45, respectively). Both approaches produced the same percentage of errors for coniferous trees (34%), most of which were errors of omission. VWF produced a higher percentage of errors for trees in the street plot (47%) than in the park plot (36%), while the opposite was true for MSI, with 44% errors in the park plot and 10% for the street plot. The majority of errors in the park plot for both approaches were errors of omission (48 out of 53 errors for VWF and 54 out of 64 for MSI), while in the street plot, commission was the most common error type for VWF (60 out of 67 errors) and omission was most common for MSI (10 out of 14 errors). MSI had a higher percentage of error for young trees (20%) than VWF (8%), although both methods had a higher percentage of error for mature trees than young trees (50% for VWF and 29% for MSI). Omission was the most common type of error for MSI for mature trees (60 out of 66 errors), while omission and commission errors were evenly spread for VWF (51 and 62 out of 115 errors, respectively). In all categories, VWF and MSI missed the same number of trees.

Discussion

VWF performance

Across both plots, the VWF approach generated 377 segments, which is 88 more than the number of actual trees present (289). This indicates over-segmentation of the trees, which is associated with errors of commission (the segmentation of non-existent trees). Commission errors produced by the VWF were especially common for deciduous trees and for trees in the street plot (which contained mostly deciduous trees). The accuracy of the VWF approach is contingent on the successful identification of tree tops. Although the purpose of the search window is to filter non-tree top local maxima, VWF is still susceptible to misidentifying branches as tree tops, particularly for deciduous trees with uneven horizontal crown profiles (Popescu & Wynne, 2004).

When divided according to category, however, omission errors were the most common type of error for coniferous trees and trees in parkland. If two tree tops are located close to one another, there is a chance that the shorter of the two will be missed by the search window (Chen et al., 2006). As such, trees with a single apex and trees in dense clusters are sources of omission errors for VWF. This is reflected by the high number of omission errors for conifers and for trees in the park plot, where a cluster of tightly-spaced Western redcedar was located.

MSI performance

The MSI approach generated 270 segments, 19 less than the total number of trees. This signals the occurrence of omission errors, where a single segment captures multiple tree crowns. Omission errors were the most common type of error for MSI in all categories except for trees under 20 years of age. From a methodological perspective, omission errors occur when the MSI algorithm fails to replace coarse-scale segments with fine-scale ones (Jing et al., 2012). This can be because the fine-scale segments were too small or because the coarse-scale segment's shape sufficiently resembled that of a tree crown. In this respect, the algorithm's performance can be adjusted by raising its k_m parameter (minimum allowable thinness ratio for a coarse segment), or by lowering its A_m parameter (minimum allowable area for a fine-scale segment).

The sharpest difference in the MSI's performance was between the two test plots, which suggests that the accuracy of the MSI approach is strongly affected by the level of clustering in urban trees. Street trees, which are planted at regular intervals along roadways and which are submitted to frequent pruning, form wide, evenly-shaped crowns that are mostly detached from each other. These appear to be ideal conditions for MSI, which detected trees in this plot with a high rate of success (90%). Within the dense cluster of trees in the park plot, many irregularly-shaped crowns were not distinguished from each other, resulting in an error rate of 44%.

Comparisons between both methods

By generating a number of segments closer to the actual number of trees, and by producing fewer total errors, the MSI outperformed the VWF approach in this study. The exceptions to this was for trees in the park plot and for trees under 20 years of age, where 8% and 12% fewer trees were associated with errors than for the MSI method respectively; and for coniferous trees, where both algorithms produced the same number of errors.

The MSI algorithm produced half as many errors for deciduous trees than the VWF. These results support previous research into MSI approaches, which have shown it to be an effective method for delineating deciduous trees (Jing et al., 2012), whose irregular crown outlines and horizontal profiles make them challenging for methods such as VWF (Chen et al., 2006). Given the relative abundance of deciduous trees planted in urban environments, this may make MSI an appealing method from a management perspective.

An important consideration when applying automated detection algorithms in an urban environment is the wide variety of tree species that are planted in cities. Previous research into VWF has noted that its effectiveness is reduced when used on mixed forest types (Popescu & Wynne, 2004). This drawback can be attenuated by using multiple sets of calibration parameters, each adapted to a specific species or group of species. In this study, GIS data maintained by the city authorities could supply the information needed for species-specific calibration, although such data may not be available in all urban areas. In these situations, MSI, which is less sensitive to variations in species, may be preferable.

Both algorithms performed better for young trees than mature trees. These results contrast with the performance of automated detection and delineation algorithms in forest stands, where young trees are often overshadowed by mature ones, making them difficult to detect (Koch, Heyder, & Weinacker, 2006). While this may hold true for smaller urban trees located near clusters of mature trees, planting crews may try to provide young trees with favorable growing conditions by placing them in open areas. One potential impediment to the detection of juvenile trees is the resolution of the canopy height model and the point density of the LiDAR from which it is derived. While the high point density of the data used in this study (average of 25 points/m^2) was sufficient to detect trees with crowns as small as $1m^2$, lower point densities may be an obstacle to successful urban tree detection in other situations.

Conclusion

Many aspects of urban forest management are conducted at an individual-tree level, making successful detection and delineation of individual trees critical if LiDAR is to be used as a viable source of information for city managers. A wide range of detection and delineation algorithms have been developed for forest stands, but few of these techniques have been tested in urban settings. Here, two such algorithms, variable window filtering (VWF) and multi-scale integration (MSI) are applied to two urban tests plots. Their accuracy is evaluated in terms of producing errors of omission (including multiple trees in a single segment), commission (generating multiple segments for a single tree) and missing trees. Their performances are then compared across various tree categories.

MSI performed better, on average, than VWF, although substantial variation existed in their performances across different categories. MSI generated fewer segments (270) than the actual number of trees (289), indicating a tendency for MSI to under-segment urban trees. The opposite was true for VWF, which generated 377 segments. For both methods, mature trees were more problematic than juveniles. MSI performed substantially better for deciduous trees, which may make it particularly suitable for urban applications where the number of deciduous trees is high. VWF produced less errors in the park plot, while MSI was more accurate in the street plot.

The relative strengths and weakness of both algorithms are revealed through this comparative study. Although both methods require parameterization, which has a strong effect on accuracy, the need to calibrate VWF based on species-specific allometric relationships may be a limiting factor in its use in urban forestry. Based on the results presented here, MSI may be a preferable approach to urban tree detection and delineation. While the wide range of tree species and age classes present in urban areas present a challenge to the successful application of these algorithms, further research into the possibility of data fusion with GIS data could reveal opportunities to improve their accuracy.

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